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Preferences for drought risk adaptation support in Kenya: Evidence from a discrete choice experiment and three decision-making theories

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ABSTRACT

Promoting household-level adaptation measures is an important part of climate change adaptation policies to reduce vulnerability to droughts for (agro-)pastoral communities in sub-Saharan Africa. To develop effective supportive policies, it is important to get a better understanding of the needs in the communities. In this study, we, therefore, present the results of a discrete choice experiment in which we identify preferences for four different support types of drought adaptation in (agro-)pastoral communities in Kenya. We include four types of drought and adaptation support: water supply, emergency livestock fodder, adaptation subsidies, and adaptation training. A novelty of our study is that we link the results from our discrete choice experiment to behavioural factors of three established decision-making theories: expected utility theory, protection motivation theory and theory of planned behaviour. Including these theories in our analysis results in an improved understanding of the causal relationship between adaptation behaviour and preferences for adaptation support. We demonstrate that households in (agro-)pastoral communities are willing to pay for both adaptation support and emergency drought support. There is however clear heterogeneity in preferences for support related to behavioural factors. We discuss the implication of our results for drought risk adaptation policy.

1. Introduction

The 2020–2023 drought in Kenya, Ethiopia and Somalia has been the worst in 70 years and has resulted in more than 23.5 million people facing acute food insecurity (UNOCHA, 2023). This region has experienced a sharp decrease in rainfall and an increase in temperature in the last decades, which has had a severe impact on rural communities that are for a large part dependent on rainfed agriculture (Funk et al., 2019; ICPAC/WFP, 2018; Liebmann et al., 2014). The government of Kenya has committed to investing in reducing the drought risk vulnerability of communities in arid and semi-arid counties (NDMA, 2014; Thomas et al., 2020). An important part of increasing drought resilience is adaptation at the household level. The government of Kenya, therefore, promotes climate-smart agriculture and livelihood diversification strategies (GoK., 2016). However, adaptation policies at the national level do not necessarily lead to effective implementation at the local level. To develop adaptation policies that are effective at the local level, it is important to consider the adaptation preferences and needs of rural households (Forsyth, 2013). The aim of this study is, therefore, to identify preferences for different types of drought adaptation support in (agro-)pastoral communities, and how these preferences differ with individual perceptions and attitudes towards adaptation. By providing insights into which population subgroups prefer specific types of adaptation support and which do not, governmental adaptation policies can be designed more effectively.

To elicit preferences for different types of drought adaptation support, we conducted a discrete choice experiment with 502 households in (agro-)pastoral communities in Kenya. Discrete choice experiments are a useful method because they allow to elicit preferences for multiple hypothetical adaptation support attributes, for which no functional markets exist (Hoyos, 2010). Previous studies in Kenya have used discrete choice experiments to elicit preferences of pastoralists or smallholder farmers for grazing management practices (Lutta et al., 2020), sand dam projects (Nthambi et al., 2021), and combinations of government policies that aim to stimulate adaption behaviour (Wens et al., 2021). Related studies in other countries have used discrete choice experiments to elicit preferences for climate-smart agriculture in Malawi (Schaafsma et al., 2019), drought risk management in India (Ward and Makhija, 2018) and climate change adaptation programmes in Nepal (Khanal et al., 2018). These studies are empirically driven without incorporating

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behavioural factors from established decision-making theories to explain choices. Several empirical studies on adaptation behaviour do however demonstrate the relevance of economic or psychological decision-making theories in explaining adaptation behaviour (Gebrehiwot and van der Veen, 2021; Schrieks et al., 2023; Van Duinen et al., 2015), and choice experiment studies in other contexts, show that decision-making theories can help to to explain heterogeneity in choices (Barkmann et al., 2008; Mu et al., 2023; Ornelas Herrera et al., 2024; Scarpa and Thiene, 2011; Shan et al., 2019). Using these theories can help to get a better understanding of the causal factors driving adaptation decisions (Kuhlicke et al., 2023; Waldman et al., 2020).

In this study, we combine survey questions on decision-making theories with the results of our discrete choice experiment on preferences for adaptation support programmes. We include drivers of adaptation behaviour from three theories: (1) expected utility theory (EUT), in which the choice of adaptation measures depends on, among others, risk attitudes and access to financial resources (Schoemaker, 1982; Sen, 2008; Von Neumann and Morgenstern, 1947); (2) the protection motivation theory (PMT), in which the intention to adapt depends on risk appraisal and coping appraisal (Maddux and Rogers, 1983; Rogers, 1983); and (3) the theory of planned behaviour (TPB), which includes attitudes towards drought adaptation, subjective norms and perceived behavioural control (Ajzen, 1991, 2002b). By combining the choice experiment data with the factors from these decision-making theories, we aim to get a better understanding of the relation between the adaptation decision-making process and the preferences for support. Understanding this relation can help to inform the effectiveness of different types of adaptation policies for distinct groups of people.

2. Study area and methods

2.1. Study area and policy context

We collected our data in Oldonyiro Ward and Burat Ward in the west of Isiolo County, Kenya (Fig. 1) in May 2022. Isiolo is a county in the Kenyan drylands, where over 80 % of the population keeps livestock as their main livelihood activity (MoALF, 2018). The county is hot and dry with irregular rainfall and frequent droughts (GoK, 2018; MoALF, 2018). Oldonyiro Ward is in the arid climate zone of the county, in which the vast majority of people live in pastoral communities, Burat Ward has arid and semi-arid zones in which more communities changed from pastoral to sedentary agro-pastoral activities (GoK, 2018; MoALF, 2018).

To increase drought resilience, the national and county governments are promoting household adaptation measures involving climate-smart agriculture techniques, livelihood diversification strategies and water harvesting methods (GoK., 2016; GoK, 2018). Some examples of commonly applied adaptation strategies in Isiolo County are diversifying livestock species, poultry farming, beekeeping, pasture conservation, starting kitchen gardens, and rainwater harvesting (Quandt, 2021; Schrieks et al., 2023). To promote the uptake of such adaptation strategies, the Isiolo County government provides subsidies for adaptation inputs and offers training and extension services (GoK, 2018). Other governmental adaptation policies to reduce drought vulnerabilities include, among other things, investments in fodder reserves and investments in water supply infrastructures (GoK, 2018).

2.2. Experimental design

We use a discrete choice experiment to elicit preferences for different types of adaptation support. In the experiment, participants receive choice cards in which they make a choice between two different types of support programs and an opt-out option (no support). We first present hypothetical information on the probability of droughts in the coming five years. We use two different scenarios. Half of the respondents received scenario one in which 4 out of 10 rainy seasons are expected to fail and the other half received scenario two, in which 8 out of the 10 rainy seasons are expected to fail.[1]

Subsequently, we explain that the government and NGOs are developing support programs to help with the implementation of adaptation measures that can make them less vulnerable to droughts. We ask participants to imagine that they can participate in a five-year support program. The support program consists of five elements, four types of drought- and adaptation support, and a monthly fee to participate. These five elements are the attributes of our choice experiment. Table 1 provides an overview of all attributes and attribute levels with the pictures used to present them to our participants.

The first attribute is an investment in a borehole near the community. The levels of this attribute are the increase in water availability, which can be 0, 5, 10 or 15 jerry cans (20 l per jerry can) per household per day, depending on the type of borehole. The levels are based on focus group discussion and a pre-test of the household survey, in which we asked people about the amount of water they get from boreholes and other water sources. Focus group discussion showed that a common way to govern these boreholes is through community commissions. Therefore, we also tell the participants that a condition for the construction of the borehole is that a community commission takes responsibility for the maintenance and management of the borehole. To get water from the borehole, every household must pay a monthly fee to this community commission to cover the maintenance costs. The second attribute is supplementary livestock feeds (fodder), which will only be provided in case of pasture shortage during a drought. The supplementary livestock feeds are provided in 10 kg hay units, and the levels are 0, 5, 10 or 15 units per week. The third attribute is a one-time subsidy for drought risk adaptation measures that will be provided at the start of the support program, which can only be used to invest in one of the following six drought risk adaptation strategies: 1) seeds for drought-resistant crops, 2) kitchen garden equipment, 3) poultry farming equipment, 4) rainwater harvesting equipment, 5) beekeeping equipment, and 6) livestock insurance.[2] The levels for the subsidy are 10,000, 20,000 or 30,000 Kenyan Shillings (KSh). The fourth attribute is a training by an NGO in which participants learn how they can use the adaptation strategy that they spent their subsidy on. This is a binary attribute, either there is a training included in the support program or there is no training included. The fifth attribute is a monthly fee that has to be paid for the full five years of the support program. The levels for the monthly fee are, 100, 300, 500, 700, 900 or 1100 KSh. This final attribute is the cost attribute that we use to calculate the willingness to pay (WTP) for the other attributes.

For the design of the choice cards, we generated a D-efficient design using Ngene software. The design consists of 12 choice cards split into three versions, meaning that each respondent received four choice cards. A D-efficient design reduces standard error in estimation, but parameter priors are needed to generate this efficient design (Bliemer and Rose, 2011). We used priors based on a pilot of our choice experiment that we conducted in March 2022. In the pilot, we collected data from 40 households, with each household receiving 8 choice cards. In total, we thus have 320 choices from the pilot, which we analysed using a multinomial logit (MNL) model. The attribute levels in the choice cards for the pilot were the same as in the final choice experiment (Table 1). Except for the monthly fee attribute, for which we included a few additional levels with higher monthly fees because we found out in the pilot that the monthly fee levels were too low.

[1] A normal year in this region has two rainy seasons: March–April-May (MAM) and October–November-December (OCD), in a period of five years they would thus expect to have 10 rainy seasons.

[2] At the end of the choice experiment we asked respondents how likely they think it is that they would invest in these six measures if they would receive support. The analysis of this data can be found in Appendix B.1

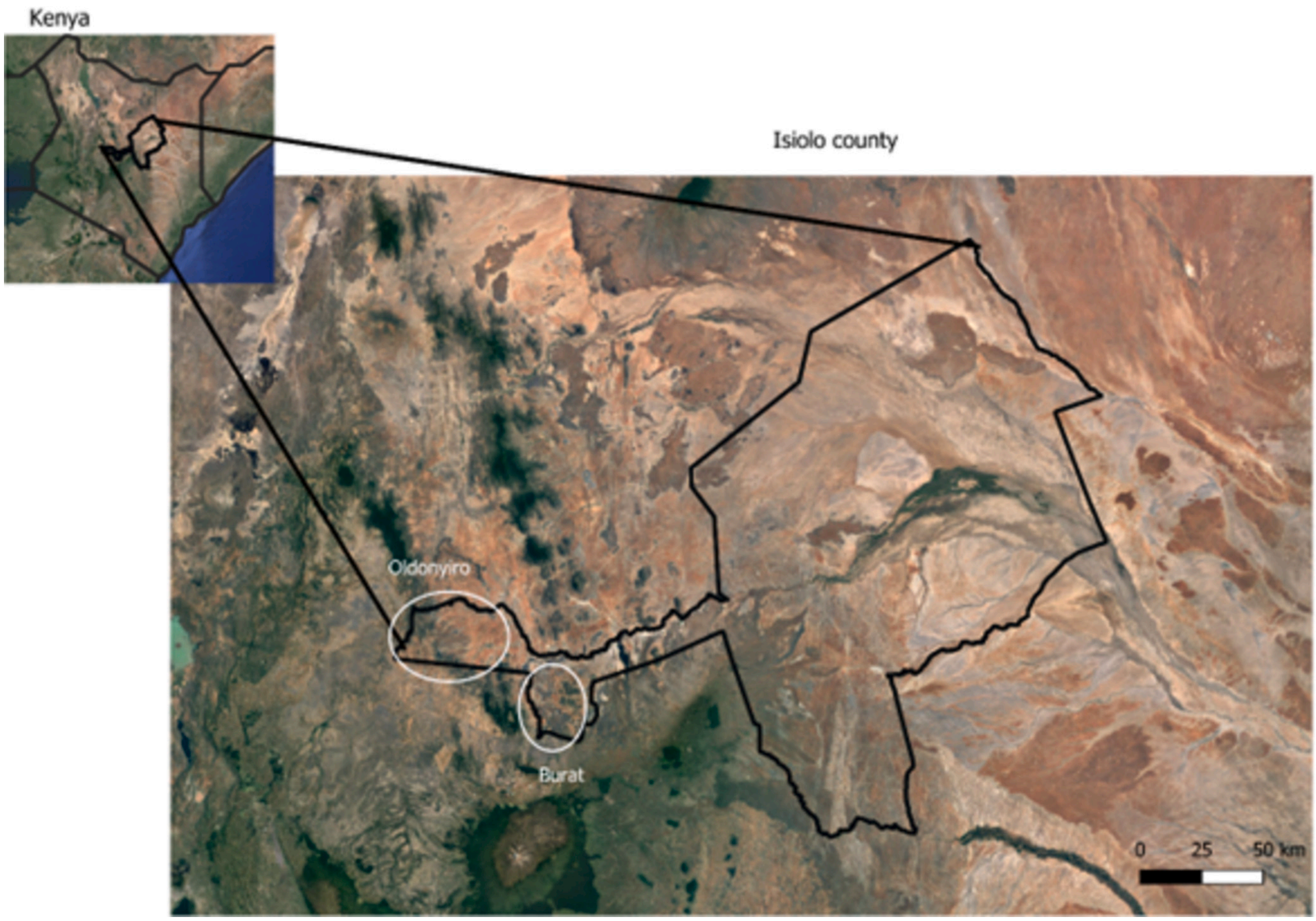

Fig. 1. Map of Kenya and Isiolo County.

2.3. Theory and hypotheses

The data collection for the choice experiment was part of a larger household survey which included questions on, among other things, adaptation decisions and intentions, and questions based on several economic and psychological decision making theories. We combine this survey data with the choice experiment data to analyse how the economic and psychological factors that are included in these theories can help to explain preferences for support. We have selected three theories that have often been used to analyse adaptation behaviour in similar contexts. The first theory is the expected utility theory (EUT). According to this economic theory, people make decisions by evaluating all possibilities and selecting the option that gives them the highest expected utility (Machina, 2008; Sen, 2008; Von Neumann and Morgenstern, 1947). The main factors determining the expected utility are expected costs and benefits, risk perceptions and risk attitudes Pervious studies have found that especially risk attitudes are an important drivers of adaptation decisions (Asravor, 2019; Brick and Visser, 2015; Holden and Quiggin, 2017; Jin et al., 2016; Liu, 2013; Ward and Singh, 2015) The second theory is the protection motivation theory (PMT). According to this theory, someone's intention to adapt depends on risk (or threat) appraisal and coping appraisal (Maddux and Rogers, 1983; Rogers, 1983). In the context of drought risk adaptation, risk appraisal is a combination of the perceived probability that a drought will occur and the perceived severity of the drought if it occurs. Coping appraisal is a combination of the perceived costs of adaptation, the perceived efficacy of adaptation, and the perceived self-efficacy, which is a person's belief in their ability to implement adaptation measures. Several studies find that both the coping appraisal and risk appraisal factors of PMT can be important in adaptation decisions for farmers in low-and-middle income countries (Delfiyan et al., 2021; Gebrehiwot and van der Veen, 2021; Keshavarz and Karami, 2016; Wens et al., 2021). The third theory is the theory of planned behaviour (TPB). TPB measures the intention to adapt as a combination of attitudes towards adaptation, subjective norms and perceived behavioural control (Ajzen, 1991). This theory has been applied in the context of climate change and drought risk adaptation by among others Arunrat et al. (2017), Zhang et al. (2020), and Faisal et al. (2020).

This study builds on Schrieks et al. (2023) in which the same survey data is used to assess economic and psychological decision-making theories on adaptation behaviour. Schrieks et al. (2023) do, however, not use the choice experiment data. In Schrieks et al. (2023) we included all the constructs of the decision-making theories. In this paper, we focus on the constructs that we expect to have a relationship with preferences for adaptation support. Below we formulate nine hypotheses on the relation between theory constructs and preference for the support attributes in the choice experiment.

The first two hypotheses are about past adaptation behaviour and future adaptation intention. Participants are asked for 15 adaptation measures if they have already implemented these measures, and which measures they are planning to implement in the coming five years. Based on the economic concept of decreasing marginal utility, we expect that the value of additional adaptation measures decreases when people have already implemented several adaptation measures (Black, 1990). Therefore, we expect that people who have already implemented many adaptation measures have a lower willingness to pay to participate in the support program and that they have a lower valuation for subsidies and training. For people with a high intention to adapt, we expect a high valuation of both training and subsidy and a higher willingness to pay for participating in the support program because they would like to

Table 1
Overview of attributes and attribute levels of the discrete choice experiment.

Attribute	No support	Level 1	Level 2	Level 3
Water supply	+0	+5/day	+10/day	+15/day
Supplementary livestock feeds during drought 10KG	+0	+5/week	+10/week	+15/week
Subsidy for drought risk adaptation strategy	X	10 000 KSh	20 000 KSh	30 000 KSh
Training	X	✓		

	No Support	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
Monthly fee	0	100 KSh/month	300 KSh/month	500 KSh/month	700 KSh/month	900 KSh/month	1100 KSh/month

Source icons: Flaticon.com

receive support for adaptation. We formulate the following two hypotheses for the relationship between adaptation behaviour and preferences for support:

Hypothesis 1. People who have already implemented many adaptation measures have a lower WTP for participating in the support program and have a lower valuation for subsidy and training.

Hypothesis 2. People with a high intention to adapt have a higher WTP for the support program and have a higher valuation for subsidy and training.

An important construct in the EUT is risk aversion (Von Neumann and Morgenstern, 1947). Risk averse people would like to reduce risks; therefore, we expect a positive correlation between risk aversion and preferences for water supply and emergency fodder, which are purely drought risk-reducing measures. Subsidies and training are support types that do not directly reduce drought risk but can help to implement adaptation measures that are also supposed to reduce risk. The relationship between adaptation and risk aversion is a bit ambiguous, several studies find that risk averse people are more likely to implement certain types of adaptation measures (Asravor, 2019; Holden and Quiggin, 2017; Jin et al., 2016; Ward and Singh, 2015), while other studies find the opposite effect for other types of adaptation measures (Asravor, 2019; Brick and Visser, 2015; Jin et al., 2016; Liu, 2013). In Schrieks et al. (2023) we did however find that risk averse people on average implement more adaptation measures. Receiving training and subsidy reduces the risk of investing in adaptation measures. Therefore, we expect a positive relation between risk aversion and preferences for training and subsidy.

Hypothesis 3. Risk aversion is positively correlated with preferences for water, fodder, subsidy, and training.

Another important factor in EUT is the budget constraint (Schrieks et al., 2021; Von Neumann and Morgenstern, 1947). People are only able to implement adaptation measures if they have enough financial resources. People with more financial resources also are less in need of government support than people who have little access to financial resources. We therefore expect a negative correlation between access to financial resources and preferences for all four types of support.

Hypothesis 4. Access to financial resources is negatively correlated with preferences for water, fodder, subsidy, and training.

According to PMT, both perceived self-efficacy and perceived adaptation efficacy should be positively correlated with the intention to adapt (Maddux and Rogers, 1983). We therefore also expect a positive relation between those two factors and the preferences for adaptation subsidy. Because of this, we also expect a positive correlation between perceived adaptation efficacy and training. We do, however, not expect this relationship between perceived self-efficacy and training. People with a high perceived self-efficacy believe that they can implement measures themselves already without training. Therefore, we expect a negative correlation between perceived self-efficacy and preference for training.

According to the PMT, a higher risk appraisal should also lead to a higher intention to adapt (Rogers, 1983). Furthermore, we expect a positive correlation between risk appraisal and preferences for water supply and emergency fodder supply, because if people are more aware of the risks of a drought, they are also more in need of water and fodder support.

Hypothesis 5. Perceived self-efficacy is positively correlated with preferences for subsidy and negatively correlated with preferences for training.

Hypothesis 6. Perceived adaptation efficacy is positively correlated with preferences for subsidy and training.

Hypothesis 7. Risk appraisal is positively correlated with preferences for water, fodder, subsidy, and training.

According to TPB, a positive attitude towards adaptation and subjective norms that promote adaptation should lead to a higher intention to adapt (Ajzen, 1991). We, therefore, expect that people with a positive attitude towards adaptation and people who experience adaptation in their social network (which we use as a proxy for subjective norm) have a higher valuation for both subsidy and training. The third factor in TPB, perceived behavioural control, is very similar to perceived self-efficacy (Schrieks et al., 2021). We use the same variable for those two factors; thus, we expect the same correlations as in Hypothesis 5.

Hypothesis 8. Attitude towards adaption has a positive correlation with preferences for subsidy and training.

Hypothesis 9. Adaptation in the social network has a positive correlation with preferences for subsidy and training.

2.4. Econometric analysis of the choice experiment data

With the data from the discrete choice experiment, we estimate a choice model based on the random utility model (McFadden, 1973). The main assumption of the random utility model is that participants choose the alternative that maximises their utility. The utility of individual i for support alternative t (U_{it}) can be expressed as $U_{it} = \beta' X_{it} + \varepsilon_{it}$, where X_{it} is a vector with the attributes of the support program, β is a vector with coefficient estimates and ε_{it} is an error term that is assumed to follow an identically and independently distributed Gumble distribution (Mariel et al., 2021).

We analyse the choice experiment data using a mixed logit model (McFadden and Train, 2000). First, we estimate the model in preference space. For the preference space model, we formulate the utility function of individual i for alternatives 1,2 and 3 (V_{it}) as follows:

$$V_{i,t=1,2} = \beta_{w,i}\text{Water} + \beta_{f,i}\text{Fodder} + \beta_{s,i}\frac{\text{Subsidy}}{1000} + \beta_{t,i}\text{Training} + \beta_{mf,i}\frac{\text{Monthly fee}}{100} \tag{1}$$

$$V_{i,t=3} = \beta_{ASC,i} \tag{2}$$

Second, we estimate the model in WTP space. For this model, we multiply the coefficients of each attribute with the coefficient of the price attribute (β_{mf}), which results in the following utility functions:

$$Vwtp_{i,t=1,2} = -\beta_{mf,i}*\left(v_{w,i}\text{Water} + v_{f,i}\text{Fodder} + v_{s,i}\frac{\text{Subsidy}}{1000} + v_{t,i}\text{Training} + \frac{\text{Monthly fee}}{100}\right) \tag{3}$$

$$Vwtp_{i,t=3} = -\beta_{mf,i}*v_{ASC,i} \tag{4}$$

In both the preference space and WTP space utility functions, we rescale the *subsidy* and *monthly fee* variables by dividing them by 1000 and 100, respectively, to prevent that parameter estimates become too small. The subsidy coefficients are thus expressed in 1000 Kenyan Shillings (KSh) and the monthly fee and WTP space coefficients are expressed in 100KSh.

After estimating the mixed logit models with only the experiment attributes, we estimate several models in which we include covariate interactions. In the models with covariates, we test the hypotheses formulated in Section 2.3. Table 2 gives an overview of the variables that we use as covariates, with a description of the questions that have been used and the coding in the data analysis. Al these variables have also been used in two of our previous studies (Schrieks et al., 2023, 2024). For the first two variables we asked respondents about fifteen different adaptation measures that are common in this region. These measures are selected based on focus group discussion, expert discussions and a pretest of the survey. For the first variable (*# implemented)*, we asked how many of these fifteen measures people already had implemented. For the second variable (*proportion intended*), we asked how many of these fifteen measures people are planning to implement in the coming five years. This variable measures the number of measures that people are intending to implement as a proportion of the measures that they can still implement (15 minus the number of already implemented measures), which is based on Noll et al. (2021). The risk aversion variables is based on a framed field experiment, integrated into the household survey (Schrieks et al., 2024). The experiment is a variation of the Holt and Laury (2002) multiple price list lottery experiment. Instead of abstract lotteries, we framed our experiment as a farming choice under varying rainfall conditions, building on various previous studies with similar experiments in rural areas in low- and middle-income countries (e.g., De Brauw and Eozenou, 2014; Holden and Quiggin, 2017; Liu, 2013; Tanaka et al., 2010). The other variables are for the different elements of PMT and TPB, for which the questions are based on several previous studies (Arunrat et al., 2017; Gebrehiwot and Van der Veen, 2015; Grothmann and Patt, 2005; Keshavarz and Karami, 2016; Truelove et al., 2015; Van Duinen et al., 2015; Wang et al., 2019; Yazdanpanah et al., 2014). More information about the data collection, including a

Table 2
Overview of the variables that we use as covariates in the models.

Variable name	Questions/Description	Coding
# implemented	Which of the following adaptation measures are already implemented by you or your household? (1) Changing and diversifying livestock species from grazers to browsers, (2) Planting drought-resistant crops, (3) Pasture conservation, (4) Saving money by participating in a savings group, (5) Starting a small business, (6) Digging a borehole or shallow well, (7) Beekeeping, (8) Planting trees for agroforestry, (9) Livestock or crop insurance, (10) Starting a kitchen garden, (11) Vaccination of livestock, (12) Poultry farming, (13) Rainwater harvesting, (14) Irrigation, (15) Moving further away with livestock than normal	Sum of adaptations measures that household has already implemented (between 0 and 15)
Proportion intended	Question: Which of the 15 adaptation measures are you planning to implement in the coming five years? # intended = sum of measures that participant is planning to adapt in the coming five years Proportion intended = # intended/ (15 - # implemented)	Proportion between 0 and 1
Risk aversion	Risk aversion levels based on a hypothetical lab-in-the-field experiment; a description of the experiment can be found in Appendix A.	Risk aversion levels (RA) between −1.95 and 1.57, with RA < 0 is risk seeking, RA = 0 is risk neutral, RA > 0 is risk averse.
Expected frequency drought	How often do you expect a drought to occur in the region where you live?	10-point Likert scale from 'Once every 10 rainy seasons or less' to 'Every rainy season'
Relative drought impact	If you compare your family situation to the rest of the community, do droughts affect you less or more than an average family?	5-point Likert scale from 'A lot less than others' to 'A lot more than others'
Perceived self-efficacy	For each of the fifteen adaptation measures we asked: To what extent do you feel able to implement the following measure that reduces the impact of drought on your household?	Composite variable with the average from 5-point Likert scales from 'not able et all' to 'very able'
Perceived adaptation efficacy	For each of the fifteen adaptation measures we asked: How effective do you think the following adaptation measure is to reduce and possibly prevent the drought impacting your livestock, crop harvest, and your life?'	Composite variable with the average from 5-point Likert scales from 'not able et all' to 'very able'
Attitude	To what extent do you agree with the following statements? 1) Implementing drought adaptation measures in the next five years is important for me and my household. 2) Adaptation measures are useful for my household to apply in the next five years	5-point Likert scale from 'strongly disagree' to 'strongly agree', The average value of the two questions. (Cronbach's α = 0.873)
Subjective norms	To what extent do you agree with the following statements? 1) Most people who are important to me think that I should invest in drought risk adaptation measures. 2) If I implemented drought risk adaptation measures, people who are important to me would approve. 3) Most people who are important to me think that investing in drought risk adaptation measures is desirable.	5-point Likert scale from 'strongly disagree' to 'strongly agree', The average value of the three questions. (Cronbach's α = 0.877)
Adaptation by family and friends[a]	Of the adaptation measures your household has implemented, how many are also implemented by other family members and friends?	5-point Likert scale from 'None' to 'All of them'
Access to credit	To what extent do you feel that you have sufficient access to the following resources to cope with droughts? Loans	4-point Likert scale from 'No access et all' to 'More than sufficient access'
Access to savings	To what extent do you feel that you have sufficient access to the following resources to cope with droughts? Savings	4-point Likert scale from 'No access et all' to 'More than sufficient access'
Access to VSLA	To what extent do you feel that you have sufficient access to the following resources to cope with droughts? Village savings and loan associations	4-point Likert scale from 'No access et all' to 'More than sufficient access'
Access to credit and savings	Average of access to credit, access to savings, and access to VSLA.	Average of three Likert scale variables, with a minimum of 1 and a maximum of 4.

[a] The correlation between the subjective norm questions and the attitude questions is too large, which creates multicollinearity issues. We therefore use adaptation by family and friends as a proxy for subjective norm instead of the questions about the norms itself in the main TPB model. We however also estimate a model with the subjective norm questions where we exclude attitude, which we use a robustness check for the model with adaptation by family and friends as a proxy for subjective norms.

more detailed explanation of the risk aversion experiment, can be found in Appendix A.

The mixed logit models are estimated using maximum likelihood estimation with the Apollo package in R (Hess and Palma, 2019). For all models we use 2000 random Sobol draws (Czajkowski and Budziński, 2019). We use the Akaike Information Criteria (AIC) to compare the performance of each model (Cavanaugh and Neath, 2019). To compare the AIC scores, we need equal sample sizes, therefore we impute missing values for the covariates that contain missing values. The missing values are never more than 2.4 % (Table 3). We can therefore safely use simple median imputation since it is unlikely to create biases (Dong and Peng, 2013; Jakobsen et al., 2017).

3. Results

3.1. Descriptive statistics

We have survey data from 502 adults, each from a different household in (agro-)pastoral communities. To get a representative sample, we employed a stratified sampling method for which we divided the population into six subgroups based on gender age categories (18–29, 30–49, and 50+) and location, based on data for Isiolo County from the Kenya Population and Housing Census of 2019 (Kenya National Bureau of Statistics, 2019). The main reason to use a stratified sample instead of simple random sampling is that young men are often away with the cattle, while the women and older men stay behind in the village. Selecting households based on simple random sampling would have led

Table 3
Descriptive statistics.

Variables		Mean	Std. Dev.	N
Age	Age in years	36.52	13.45	502
Gender	Female = 1, Male = 0	0.52		502
Burat Ward	1 = Burat Ward, 0 = Oldonyiro Ward	0.54		502
# implemented	Number of implemented measures between 0 and 15	2.71	1.79	501
Proportion Intended	Proportion of intended measure from measures that are not implemented yet.	0.23	0.19	500
Risk aversion	RA < 0 is risk seeking, RA = 0 is risk neutral, RA > 0 is risk averse.	0.63	0.88	490
Perceived self-efficacy	Average of 15 questions with 5-point Likert scales	2.83	1.08	500
Perceived adaptation efficacy	Average of 15 questions with 5-point Likert scales	3.98	0.66	496
Expected frequency drought	Once every 10 rainy seasons or less = 1 to every rainy season = 10	8.94	1.03	501
Relative drought impact	A lot less than others = 1 to a lot more than others = 5	3.16	0.69	502
Attitude	Average of two questions with 5-point Likert scales	4.48	0.59	494
Adaptation by family and friends	5-point Likert scale from 'None' to 'All of them'	2.70	0.82	490
Subjective norms	Average of three questions with 5-point Likert scales	4.31	0.64	492
Access to credit	No access at all = 1, too little access =2, sufficient access = 3, more than sufficient access = 4	1.76	0.88	494
Access to Savings	No access at all = 1, too little access =2, sufficient access = 3, more than sufficient access = 4	1.99	0.89	502
Access VSLA	No access at all = 1, too little access =2, sufficient access = 3, more than sufficient access = 4	2.27	1.01	499
Household head	1 = head of the household, 0 = not the head of the household	0.71		502
Crop farming	1 = Practices crop farming, 0 = Does not practice crop farming	0.19		502
Livestock keeping	1 = Keeps livestock, 0 = Does not keep livestock	0.71		502
Small business	1 = has a small business, 0 does not have a business	0.24		502
Poultry farming	1 = practices poultry farming, 0 = does not practice poultry farming	0.26		502

to an underrepresentation of young men and an overrepresentation of women and older men. Table 3 shows the descriptive statistics of the sample. We observe that both the mean number of implemented measures and the mean proportion of intended measures are relatively low, while the mean perceived adaptation efficacy and attitude towards adaptation are quite high, so there seems to be quite some potential to increase adaptation uptake. Respondents expect droughts to occur very often (high mean expected frequency of drought), which might be influenced by the fact that the survey was conducted in May 2022, which was in the middle of a severe drought (WFP, 2023). We observe that respondents have on average little access to financial resources, but access to Village Saving and Loan Associations (VSLA) is a bit better than access to credit and access to savings. Most of our respondents (71 %) are the head of their household, but we also have 29 % respondents that are not the head of their household. Most of the people in our sample live from livestock keeping (71 %), but we also have people who engage in small scale crop farming (19 %), people who have a small business (24 %) or people who practice poultry farming. People can have multiple sources of income and can combine the aforementioned livelihood activities. Besides these four main activities some people also get some income from, among other things, bee keeping, kitchen gardens, charcoal burning and some wage labour.

Table 4
Mixed logit models in preference space and WTP space.

	Model 1: Preference space		Model 2: WTP space	
Fixed parameters	Coefficient (Rob. S.E.)		Coefficient (Rob. S.E.)	
Monthly fee (in 100 KSh)	−0.057*** (0.011)		−0.058*** (0.011)	
Random parameters	Mean (Rob. S.E.)	S.D. (Rob. S.E.)	Mean WTP (Rob. S.E.)	S.D. WTP (Rob. S.E.)
Water	0.117*** (0.014)	0.158*** (0.018)	2.051*** (0.398)	−2.767*** (0.562)
Fodder	0.038*** (0.009)	−0.054*** (0.015)	0.662*** (0.167)	0.952*** (0.306)
Subsidy	0.027*** (0.005)	0.028** (0.012)	0.467*** (0.103)	0.503** (0.224)
Training	1.153*** (0.130)	−1.290*** (0.159)	20.197*** (4.241)	22.656*** (5.012)
ASC opt-out	−31.670** (13.850)	−13.653** (5.343)	−492.037*** (205.603)	223.767*** (86.027)
N	502		502	
Observations	2004		2004	
Log likelihood	−1208.36		−1208.21	
AIC	2438.72		2438.42	
Adjusted ρ^2	0.4462		0.4462	
Number of draws	2000		2000	

* $p < 0.1$, **$p < 0.05$, ***$p < 0.01$ (one-sided p-values for monthly fee coefficient and means for random parameters, two-sided for standard deviations).

3.2. Mixed logit model

Table 4 presents the results of the mixed logit model in preference space (Model 1) and WTP space (Model 2). In these baseline models, the coefficient for *monthly fee* is kept fixed, and all other parameters follow a random normal distribution.[3] We also estimated a model with all parameters following a random normal distribution (Appendix B2, Table B2, Model B1), but the standard deviation for *monthly fee* is not significant in that model, which is why we keep *monthly fee* fixed in all models.[4]

The signs of all parameter coefficients in Table 4 are as theoretically expected and all estimates are statistically significant. The *monthly fee* coefficient is negative, which means that people are less likely to select a support program with a higher monthly fee. The mean coefficients for *water, fodder, subsidy,* and *training* are all positive, which means that people are more likely to select a support program that includes higher levels of water supply, more emergency fodder supply, higher subsidies, and a training. The preferences for these four support attributes do however significantly differ between respondents, which can be seen from the significant standard deviations. The standard deviations for *water, fodder, subsidy,* and *training* are all larger than the means.

The alternative specific constant (*ASC*) represents the valuation of the opt-out option. The opt-out rate in our experiment was very low, only 0.65 % of the choices. Because of this low opt-out rate, the model estimates a very large negative coefficient for the ASC. This suggests that receiving any type of support is valued much higher than not participating in a support program (the status quo situation). We do however

[3] The model in Table 4 does not include correlated coefficients. We also estimated a model in which we included correlations between all model parameters. This model can be found in appendix B2 (Table B2, Model B3). The results of the model with correlated coefficients are not significantly different.

[4] Additional analyses have been done in which we include interaction effects with control variables for household heads and for livestock keepers and crop farmers. These analyses can be found in appendix B3 and B4, these additional control variables do not improve the model fit and the results do not significantly differ from Model 1.

not put much value on the size of the ASC coefficients because the opt-out rate in our experiment is too low to get reliable estimates, which is why we do not explicitly discuss the results of the ASC parameters in the other models in this paper.

The mean WTP estimates in the WTP-space model (Table 4, Model 2) represent the mean marginal WTP in 100KSh. A mean WTP estimate for *water* of 2.051 thus means that participants are, on average, willing to increase the monthly fee by 205 KSh for one additional unit of water supply. The mean WTP for one additional unit of fodder is 66 KSh per month, for a 1000 increase in subsidy it is 47 KSh per month and for a training it is 2020 KSh per month. The marginal WTP estimates are, however, difficult to compare, because each attribute has different units. In Table 5 we, therefore, calculate the mean WTP for eight example support programs with different combinations of support. The first four programs only include one type of support, but with the maximum amount of that support type that has been included in the experiment. Based on these calculations, we conclude that water supply is, on average, valued more than emergency fodder supply. A training about adaptation measures is, on average, valued higher than a one-time subsidy with a maximum of 30,000 KSh. In support program 5 and 6 we compare moderate levels of support with and without training. Without the training the mean monthly WTP decreases with 2020 KSh from 5670KSh to 3650 KSh. In program 7 and 8 we compare a program with only water and fodder supply with a program with only adaptation subsidy and training. The estimated mean WTP is only slightly higher for the program with subsidy and training, there is no large difference.

After the baseline model runs, we estimated a model in which we added a control variable for the climate scenarios. In this model, we analysed the differences in preferences between the group who received climate scenario 1 (4 out of 10 rainy seasons are expected to fail) and climate scenario 2 (8 out of the 10 rainy seasons are expected to fail). We did not find a significant difference in the preferences for support between these two groups and controlling for the climate scenario did not result in a better model fit, which is why we do not include the climate scenarios in our further analysis. The model with climate scenarios and a discussion of the results can be found in Appendix B5.

Table 5
Mean WTP for example support programs.

	Amount of support in support program				Mean WTP (per month)	
Support scenario	Yerry cans of water per day	Weekly fodder supply (10Kg of hay)	Subsidy In KSh	Training	KSh	Euro[a]
1 Only water (maximum)	15	0	0	No	**3075**	€ 25
2 Only fodder (maximum)	0	15	0	No	**990**	€ 8
3. Only subsidy (maximum)	0	0	30,000	No	**705**	€ 11
4. Only training	0	0	0	Yes	**2020**	€ 16
5. Moderate support with training	10	10	20,000	Yes	**5670**	€ 45
6. Moderate support without training	10	10	20,000	No	**3650**	€ 29
7. Only water and fodder (moderate)	10	10	0	No	**2710**	€ 22
8. Only subsidy and training (moderate)	0	0	20,000	Yes	**2960**	€ 24

[a] Exchange rate is based on exchange rate during data collection (May 2022): 1 Kenyan Shilling = 0.008 Euro.

3.3. Preferences for support and adaptation behaviour

In Table 6, we assess the relationship between preferences for the support programs and actual adaptation behaviour and intentions.

In Model 3, we include the interaction effects of *# implemented* with *subsidy, training,* and *monthly fee* to the preference space model. In Model 4, we include the interaction effects of *proportion intended* with the same attributes. Both models have higher log-likelihood and a lower AIC score than the models in Table 2, which indicates that the model improves by including these interaction effects. For both *#implemented* and *proportion intended,* we observe a significant positive interaction effect with *training.* This means that both a high number of already implemented measures and a high intention to adapt are positively associated with a preference for training. In Model 3, we also observe a significant negative interaction effect between *# implemented* and *monthly fee*, which indicates that people who have already implemented many measures are willing to pay less for government support than people who have not implemented many measures yet.

3.4. Behavioural theory covariates

In Model 5 (Table 7), we include the interaction effects between *risk aversion* and the four support attributes. We observe a significant positive interaction effect for three out of the four support attributes. The more risk averse, the higher the valuation of water supply, emergency

Table 6
Mixed logit model in preference space with covariates for adaptation behaviour.

	Model 3: #implemented		Model 4: Proportion intended	
Fixed parameters	Coefficient (Rob. S.E.)		Coefficient (Rob. S.E.)	
Monthly fee	−0.032** (0.018)		−0.062*** (0.017)	
Random parameters	Mean (Rob. S.E.)	S.D. (Rob. S.E.)	Mean (Rob. S.E.)	S.D. (Rob. S.E.)
Water	0.121*** (0.014)	0.155*** (0.018)	0.119*** (0.014)	0.153*** (0.018)
Fodder	0.040*** (0.009)	−0.058*** (0.015)	0.039*** (0.009)	−0.057*** (0.015)
Subsidy	0.017** (0.008)	0.021** (0.010)	0.031*** (0.008)	−0.031** (0.015)
Training	0.571*** (0.176)	−0.637*** (0.194)	0.758*** (0.167)	−0.840*** (0.184)
ASC	−25.390** (9.448)	−11.117*** (3.994)	−24.417** (12.151)	10.583*** (4.543)
Interaction with	# implemented		proportion intended	
Subsidy	0.253 (0.251)		−0.382 (0.901)	
Training	0.429** (0.243)		2.525** (1.396)	
Monthly fee	−0.011** (0.006)		0.013 (0.059)	
N	502		502	
Observations	2004		2004	
Log likelihood	−1196.88		−1201.14	
AIC	2421.76		2430.27	
Adjusted ρ^2	0.45		0.4481	
Number of draws	2000		2000	

* $p < 0.1$, **$p < 0.05$, ***$p < 0.01$ (one-sided p-values for monthly fee coefficient and means for random parameters and interaction effects, two-sided for standard deviations).

Table 7
Mixed logit model with EUT covariates.

	Model 5: Risk aversion		Model 6: Risk aversion + Credit and Savings	
	Coefficient (Rob. S.E.)	Coefficient (Rob. S.E.)	Coefficient (Rob. SE)	Coefficient (Rob. SE)
Monthly fee (fixed)	−0.058*** (0.011)		−0.059*** (0.012)	
Random parameters	Mean (Rob. S.E.)	S.D. (Rob. S.E.)	Mean (Rob. S.E.)	S.D. (Rob. S.E.)
Water	0.100*** (0.012)	−0.132*** (0.017)	0.194*** (0.038)	0.252*** (0.059)
Fodder	0.028*** (0.008)	−0.038*** (0.012)	0.056** (0.028)	−0.076** (0.038)
Subsidy	0.024*** (0.006)	0.023** (0.011)	0.078*** (0.016)	0.071* (0.037)
Training	1.054*** (0.128)	−1.186*** (0.156)	1.407*** (0.341)	1.603*** (0.405)
ASC	−23.447* (5.649)	−8.973** (1.985)	−50.963 (207.090)	−22.117 (87.289)
Interaction with risk aversion (RA)				
Water * RA	0.406*** (0.106)		0.170** (0.077)	
Fodder * RA	0.759** (0.351)		0.339* (0.238)	
Subsidy * RA	0.261 (0.253)		0.036 (0.106)	
Training * RA	0.229*** (0.089)		0.162** (0.076)	
Water * C&S			−0.221*** (0.041)	
Fodder * C&S			−0.233** (0.122)	
Subsidy * C&S			−0.313*** (0.035)	
Training * C&S			−0.120* (0.076)	
N	502		502	
Observations	2004		2004	
Log likelihood	−1202.38		1189.57	
AIC	2434.76		2417.15	
Adjusted ρ^2	0.4471		0.4511	
Number of draws	2000		2000	

* p < 0.1, **p < 0.05, ***p < 0.01 (one-sided p-values for monthly fee coefficient and means for random parameters and interaction effects, two-sided for standard deviations).

Table 8
Mixed logit model with PMT covariates.

	Model 7: PMT	
Fixed parameters	Coefficient (Rob. S.E.)	Coefficient (Rob. S.E.)
Monthly fee	−0.060*** (0.011)	
Random parameters	Mean (Rob. S.E.)	S.D. (Rob. S.E.)
Water	0.001*** (0.000)	0.001*** (0.000)
Fodder	0.006 (0.021)	−0.009 (0.031)
Subsidy	0.002 (0.015)	−0.001 (0.008)
Training	7.131*** (1.391)	−6.924*** (1.257)
ASC	−31.164** (13.876)	−14.137** (5.807)
Perceived adaptation efficacy (AE)		
Subsidy * AE	−0.822 (5.421)	
Training* AE	−0.046** (0.023)	
Perceived self-efficacy (SE)		
Subsidy * SE	−1.478 (1.788)	
Training * SE	−0.030** (0.013)	
Expected frequency drought (EFD)		
Water * EFD	18.560*** (6.593)	
Fodder * EFD	0.335 (1.469)	
Subsidy * EFD	3.025 (20.711)	
Training * EFD	−0.052*** (0.010)	
Relative drought impact (RDI)		
Water * RDI	−12.071 (12.772)	
Fodder * RDI	0.699 (3.117)	
Subsidy * RDI	−2.716 (18.384)	
Training * RDI	−0.034** (0.018)	
N	502	
Observations	2004	
Log likelihood	−1176.82	
AIC	2399.64	
Adjusted ρ^2	0.455	
Number of draws	2000	

* p < 0.1, **p < 0.05, ***p < 0.01 (one-sided p-values for monthly fee coefficient and means for random parameters and interaction effects, two-sided for standard deviations).

fodder supply, and training. However, we do not find a significant relation between risk aversion and preference for subsidy. In Model 6 (Table 5), we also add interaction effects with *access to credit and savings*. This variable has a significant negative interaction effect with all four support attributes, which indicates that respondents with little access to financial resources have a stronger preference for all types of support than respondents with more access to financial resources.

In Table 8 (Model 7), we included the interaction effect with the PMT variables. For both perceived adaptation efficacy and perceived self-efficacy, we find no significant interaction effect with *subsidy* and a significant negative effect with *training*. The significant negative interaction between *training* and *perceived self-efficacy* is as expected (Hypothesis 5), participants who believe in their ability to implement measures do not need training. The interaction effect between *training* and *perceived adaptation efficacy* is however opposite from what we expected in Hypothesis 6. The results indicate that participants who think that adaptation measures are effective are less likely to select a support program with a training than participants who believe that the measures are less effective.

For the risk appraisal variables (*expected frequency drought* and *relative drought impact)*, we also observe a significant negative interaction effect with *training*, while in our hypothesis we expected a positive effect (contradicting Hypotheses 7). The final significant coefficient is a large positive interaction effect between *expected frequency drought* and *water*, meaning that people who expect a drought to occur very frequently have a strong preference for water supply (in line with Hypothesis 7).

In Table 9, we estimate the interaction effects of the TPB variables with *subsidy* and *training*. In Model 8a, we include *perceived self-efficacy*, *attitude* and *adaptation by family and friends*. The interaction between *attitude* and *subsidy* is not significant and the interaction between *attitude* and *training* is significant and positive (partly supporting Hypothesis 8), meaning that people with a positive attitude towards adaptation have a strong preference for adaptation training. For *adaptation by family and friends,* we find a significant negative interaction effect with *subsidy* and a significant positive interaction effect with *training* (partly supporting Hypothesis 9). The negative interaction effect with *subsidy* is the opposite of what we expected. In Model 8b, we included another variable measuring *subjective norm*, which is more closely related to subjective norm measures in other TPB studies (Ajzen, 2002a; Yazdanpanah et al., 2014).[5] The interaction effect of *subjective norm* and *training* is not

[5] The measures for *subjective norm* and *attitude* are highly correlated, which leads to multicollinearity issues if we include them in the same model. This is why we use *adaptation by family and friends* as a proxy for subjective norms in Model 8a and exclude *attitude* from Model 8b. Model 8b performs best (lowest AIC and log-likelihood), this is, therefore, our main TPB model. We do, however, also include Model 8b as a robustness check for the results related to subjective norms.

Table 9
Mixed logit model with TPB covariates.

	Model 8a: TPB1		Model 8b: TPB2	
	Coefficient (Rob. SE)		Coefficient (Rob. SE)	
Monthly fee (fixed)	−0.057***		−0.058***	
	(0.011)		(0.011)	
Random parameters	Mean (Rob. S.E.)	S.D. (Rob. S.E.)	Mean (Rob. S.E.)	S.D. (Rob. S.E.)
Water	0.121***	0.147***	0.118***	0.153***
	(0.014)	(0.018)	(0.014)	(0.019)
Fodder	0.040***	−0.059***	0.039***	0.059***
	(0.009)	(0.015)	(0.009)	(0.015)
Subsidy	0.090***	−0.093**	0.061*	0.052**
	(0.036)	(0.041)	(0.039)	(0.031)
Training	0.024***	0.025***	1.896***	−2.141***
	(0.024)	(0.006)	(0.755)	(0.896)
ASC	−22.442***	9.843***	−47.439**	20.244**
	(8.617)	(3.185)	(24.979)	(10.049)
Interaction with perceived self-efficacy (SE)				
Subsidy * SE	−0.033		−0.033	
	(0.041)		(0.067)	
Training * SE	−12.667***		−0.141***	
	(4.139)		(0.068)	
Interaction with attitude (A)				
Subsidy * A	−0.024			
	(0.068)			
Training * A	13.862***			
	(5.045)			
Interaction with adaptation by family and friends (AFF)				
Subsidy * AFF	−0.186***			
	(0.067)			
Training * AFF	9.249**			
	(4.289)			
Interaction with subjective norm (SN)				
Subsidy * SN			−0.105*	
			(0.076)	
Training * SN			0.006	
			(0.093)	
N	502		502	
Observations	2004		2004	
Log likelihood	−1188.22		−1202.72	
AIC	2410.45		2435.49	
Adjusted ρ^2	0.4526		0.4469	
Number of draws	2000		2000	

* $p < 0.1$, **$p < 0.05$, ***$p < 0.01$ (one-sided p-values for monthly fee coefficient and means for random parameters and interaction effects, two-sided for standard deviations).

significant, and the interaction effect of *subjective norm* and *subsidy* is significant and negative. Model 8b, thus confirms the result from Model 8a that people with a social network that is positive towards adaptation are less likely to value the subsidy.

3.5. Goodness-of-fit

To analyse the fit of the different models, we compare three goodness-of-fit statistics that are provided in the Apollo R-package (Hess and Palma, 2019). Table 10 provides the AIC scores, log likelihood (LL) and adjusted ρ2 for all the models with covariates and compares that with the statistics for Model 1 (the base model without covariates in preference space). All of the models have a lower AIC score and higher log likelihood and adjusted ρ2, than the base model, meaning that adding the different covariates improves the goodness of fit in all of the models. To test if this difference is statistically significant, we perform a Ben-Akiva and Swait test (BAS-test, Ben-Akiva & Swait, 1986). The final column in Table 10 provides the *p*-values of this test. For all models this p-value is smaller than 0.01, meaning that the goodness-of-fit is significantly better than the base model. Adding covariates of the different behavioural theories to the models does thus significantly improve the model fit and can help to get a better understanding of the drivers of the decisions that people make in the choice experiment. We also performed Ben-Akiva & Swait tests to compare model 5 and 6, which show that adding access to credit and savings significantly improves the model fit (p-value BAS-test = 1.668e-06). Furthermore, we compared Model 8a and Model 8b, which shows that Model 8a is the TPB model with the significant better fit (p-value BAS-test = 4.318e-08). The model with the best goodness-of-fit statistics is Model 8: PMT (lowest AIC, highest LL and adjusted ρ2). A Ben-Akiva & Swait test shows that this model performs significantly better than the second best model (Model 8a: TPB1, p-value BAS-test = 5.353e-05). Model 7 (PMT) also has the least significant standard errors; thus, it accounts best for heterogeneity in preferences. These results indicates that the PMT variables perceived self-efficacy, perceived adaptation efficacy and expected frequency drought are important determinants for the preferences for support.

4. Discussion

4.1. Discussion of results

In this study, we analysed data from a discrete choice experiment on preferences for four different types of government support for drought adaptation. We demonstrate that households in (agro-)pastoral communities are willing to pay for direct (emergency) drought support and for adaptation support, but that there is clear heterogeneity in preferences for support related to behavioural factors. We formulated nine hypotheses about the relationship between drought adaptation support and behavioural constructs from the expected utility theory (EUT), the protection motivation theory (PMT) and the theory of planned behaviour (TPB). Table 11 provides an overview of the results per hypothesis. We discuss the most notable results.

The first two hypotheses were not directly related to the behavioural constructs of one of the theories, but to the outcomes of adaptation behaviour. We wanted to test if there is a relationship between adaptation decisions and adaptation intentions and preferences for support. We expected that people who have already implemented adaptation measures are less in need of adaptation support therefore we

Table 10
Comparison of goodness-of-fit statistics.

	AIC	LL	Adjusted ρ^2	Parameters	Difference with Model 1: AIC	LL	Adjusted ρ^2	P-value BAS-test
Model 1: Base model	2438.72	−1208.36	0.4462	11				
Model 3: #implemented	2421.76	−1196.88	0.4500	14	16.96	11.48	0.0038	4.45E-06
Model 4: Proportion intended	2430.27	−1201.14	0.4481	14	8.45	7.22	0.0019	0.000374
Model 5: Risk aversion	2434.76	−1202.38	0.4471	15	3.96	5.98	0.0009	0.002387
Model 6: Risk aversion + Credit and Savings	2417.15	−1189.57	0.4511	19	21.57	18.79	0.0049	2.69E-08
Model 7: PMT	2399.64	−1176.82	0.4550	23	39.08	31.54	0.0088	5.25E-13
Model 8a: TPB1	2410.45	−1188.22	0.4525	19	28.27	20.14	0.0063	1.13E-09
Model 8b: TPB2	2435.49	−1202.72	0.4469	19	3.23	5.64	0.0007	0.003893

Table 11
Overview of results per hypothesis.

Hypothesis	Covariate	Significant interaction effects		Nonsignificant interaction effect
		Supporting the hypotheses	Contradicting the hypotheses	
H1: People who have already implemented many adaptation measures have a lower WTP for participating in the support program and have a lower valuation for subsidy and training.	#Implemented	Monthly fee –	Training ++	Subsidy
H2: People with a high intention to adapt have a higher WTP for the support program and have a higher valuation for subsidy and training.	Proportion intended	Training ++		Subsidy Monthly fee
H3: Risk aversion is positively correlated with preferences for water, fodder, subsidy, and training.	Risk aversion	Water +++ Fodder ++ Training +++		Subsidy
H4: Access to financial resources is negatively correlated with preferences for water, fodder, subsidy, and training.	Access to credit and savings	Water — Fodder – Subsidy — Training -		
H5: Perceived self-efficacy is positively correlated with preferences for subsidy and negatively correlated with preferences for training.	Perceived self-efficacy	Training –		Subsidy
H6: Perceived adaptation efficacy is positively correlated with preferences for subsidy and training.	Perceived adaptation efficacy		Training - -	Subsidy
H7: Risk appraisal is positively correlated with preferences for water, fodder, subsidy, and training.	Expected frequency drought	Water +++	Training —	Fodder Subsidy
	Relative drought impact		Training –	Water Fodder Subsidy
H8: Attitude towards adaption has a positive correlation with preferences for subsidy and training.	Attitude	Training +++		Subsidy
H9: Adaptation in the social network has a positive correlation with preferences for subsidy and training.	Adaptation by family and friends	Training ++	Subsidy —	

+++ postive effect $p < 0.01$, ++ positive effect $p < 0.05$, + postive $p < 0.1$. --- negative effect $p < 0.01$, -- negative effect $p < 0.05$, - negative effect $p < 0.1$

hypothesize that they would have a lower WTP for the support programs and a lower valuation of both subsidy and fodder (hypothesis 1). In line with this hypothesis, we find a negative interaction effect between monthly fee and the number of implemented measures, but we do not find a significant relation for subsidy, and for training we actually find a positive interaction effect. We expected that people who have already implemented many adaptation measures do not need to receive training anymore. None of the respondents did however already implement all the fifteen measures that were included in our survey, so they always have other measures available that they can still implement. Previous studies show that people who have already implemented some measures are more likely to implement other adaptation measures in the future (Noll et al., 2022; Schrieks et al., 2023), which could also explain why people who have already undergone several measures still would like to receive training to learn about other adaptation measures. In line with Hypothesis 2, we find that people with a higher intention to adapt have a higher valuation for training, but we do not find a significant relationship between the intention to adapt and preference for subsidy and the monthly fee.

For EUT, we focused on risk aversion (Hypotheses 3). We find evidence that risk averse people are more likely to value water supply, emergency livestock fodder and adaptation training. These findings are in line with the theoretical assumption that risk averse people prefer to reduce uncertainty by securing water and fodder supply and in line with previous studies who find that risk averse people have a higher willingness to adapt (Asravor, 2019; Holden and Quiggin, 2017; Jin et al., 2017; Ward and Singh, 2014). There are, however, also studies that find that risk averse people are less likely to implement certain types of adaptation measures (Asravor, 2019; Brick and Visser, 2015; Jin et al., 2017; Liu, 2013). In Schrieks et al. (2023) we discuss that risk averse farmers are more likely to implement adaptation measures that are a small change to their current livelihood activities and less likely to implement adaptation measures that require a big change. Adaptation measures that require a big change bring uncertainty, because people are uncertain about the outcomes and might lack the knowledge about these adaptation measures. Training might reduce this uncertainty, which could be another reason why risk averse individuals have a higher preference for training. Based on the assumption that a subsidy would reduce the risk of investments in adaptation measures, we also expected a positive relation between risk aversion and a preference for subsidy. However, we did not find evidence for this hypothesis. Besides risk aversion, we also analysed the effect of access to credit and savings. In line with Hypotheses 4, we find a negative relation between access to credit and savings and preferences for all four support attributes, probably because people with a better access to credit and savings are less in need of external support.

For PMT, the literature on agricultural drought adaptation finds that perceived adaptation efficacy and perceived self-efficacy are important drivers of adaptation decisions (Gebrehiwot & van der Veen, 2021; Schrieks et al., 2023; Wens et al., 2021). We therefore expected that a higher adaptation efficacy and self-efficacy would also correspond to a higher preference for training (Hypotheses 6 and 7), but we did not find evidence for these hypotheses. For training we actually find that a high self-efficacy and adaptation efficacy corresponds to a lower preference for training. We expected this for self-efficacy, because people who are already confident about their ability to implement measures might not need a training anymore. For adaptation efficacy this is the opposite from what we expected. We can only speculate about the explanation for this result, but the explanation could be similar as for self-efficacy. People with a higher adaptation efficacy might have more knowledge about adaptation measures and therefore, they are less in need of training. This relationship could be explored further in future literature. Furthermore, PMT expects a positive relationship between risk appraisal and the intention to adapt (Rogers, 1983). We therefore expected that people with a higher risk appraisal are more in need of training and subsidy that can help them adapt, we did however not find a significant result for subsidy, and we found the opposite relationship between risk appraisal and training. Some studies show that people with very high risk-perceptions are less likely to implement adaptation measures, especially when combined with low coping appraisal (Bubeck et al., 2018; Schrieks et al., 2023). In extreme drought conditions, as exist in our study area, adaptation limits can be reached, and adaptation measures might no longer be effective. This situation might explain why people would not value training anymore if they have a very high risk perception. As expected, we found that people with a higher expected frequency of drought have a higher valuation for water supply. We did not find a significant relationship between risk appraisal and preferences for emergency livestock fodder.

Finally for TPB, literature shows that a positive attitude towards adaptation and a social network that is positive towards adaptation leads to a higher intention to adapt (Ajzen, 1991; Arunrat et al., 2017). We therefore expected a positive relationship between attitude and preferences for training and subsidy. For training we indeed found this result, but the relationship between attitude and subsidy is not significant. Furthermore, we expected that for people who observe adaptation by family and friends it is more likely that they also want to adapt themselves (Schrieks et al., 2023), which is why we expected them to prefer training and subsidy to help them adapt. We do find this relationship for training, but we find the opposite for subsidy. A possible explanation is that people with a stronger social network can rely on their social network for support in implementing adaptation measures and are, therefore, less in need of subsidy than people with a weak social network. This could be an interesting relationship to study in more detail in future research.

It is important to note that the confirmed hypotheses do not provide evidence for the full theories, but only some of the assumptions that are part of these theories. We did not include the full theories and the variables that we included are not exclusively for one theory. For example, the risk appraisal factors that we included in PMT are often also included in applications of EUT and perceived self-efficacy is similar to the perceived behavioural control that is part of TPB (Schrieks et al., 2021, 2023).

4.2. Limitations and suggestion for future research

Our analysis only includes three established theories. These theories have been shown in previous research to be relevant in describing adaptation behaviour, but there are several other relevant theories and extension of these three theories that could have relevant variables that are not included in our analysis. Possible alternatives for EUT are rank dependent utility theory and prospect theory (Diecidue and Wakker, 2001; Kahneman and Tversky, 1979; Quiggin, 1982; Tversky and Kahneman, 1992). Instead of PMT and TPB one could use, among others, the theory of interpersonal behaviour, the social cognitive theory and the norm activation model (Bandura, 2001; Schwartz, 1977; Triandis, 1979). Wens et al. (2021) describe several relevant theories and review their use in the context of adaptation behaviour for small scale farmers. They conclude that PMT, TPB, EUT and Prospect Theory are the most applied theories, and that PMT provides the most convincing results in the context of Kenya and Africa. We are, however, aware of alternative theories that may propose other relevant explanatory variables that are not included in our models. Our analysis is not complete, but it does demonstrate that behavioural theories can help to get a better understanding of the factors that are driving the choices of respondents. Several choice experiment studies in other contexts, already show that psychological theories such as the theory of planned behaviour and the protection motivation theory can help to explain heterogeneity in choices (Barkmann et al., 2008; Mu et al., 2023; Ornelas Herrera et al., 2024; Scarpa and Thiene, 2011; Shan et al., 2019). Most choice modelling studies are, however, empirically driven and do not incorporate established decision-making theories to explain their results. Future research can test the relevance of various alternative behavioural theories in explaining individual preferences for drought risk adaptation measures.

The complex psychological constructs of the theories are measured with survey data. This is challenging, because survey questions will never be able to perfectly capture all elements of the psychological construct. The questions can only be used as a proxy. Especially the norms, values and perceptions in TPB and PMT are difficult to quantify, and guidelines for measuring these constructs are not well established (Ajzen, 2020; Kothe et al., 2019; Yuriev et al., 2020). We aim to address this challenge as well as possible by designing our survey questions based on previous studies that have applied these theories to drought adaptation behaviour (Arunrat et al., 2017; Gebrehiwot and Van der Veen, 2015; Grothmann and Patt, 2005; Keshavarz and Karami, 2016; Truelove et al., 2015; Van Duinen et al., 2015; Wang et al., 2019; Wens et al., 2021; Yazdanpanah et al., 2014). We are however aware that there could still be some biases in the results. For the measurement of risk aversion in EUT, there are well established experiments with clear mathematical formalizations (Charness et al., 2013; Holt & Laury, 2014; Tanaka et al., 2010). A challenge with these kind of experiments is however that they are often tested with students in a lab setting and can be too abstract and difficult to comprehend for applications in the field (Charness & Viceisza, 2016; Estepa-Mohedano & Espinosa, 2023; Hirschauer et al., 2014). Providing more context to the participants can reduce confusion, which leads to more reliable choices (Alekseev et al., 2017). We have therefore framed our experiment as farming decisions under drought risk conditions. With this framing we find significantly less inconsistent choices than other studies who apply abstract Holt and Laury experiments in similar field settings, which indicates that our approach is easier to comprehend (Schrieks et al., 2024). A disadvantage of the framing is that choices might be influenced by certain values and perception (Alekseev et al., 2017). We do however believe that the framing leads to more reliable results because it is easier to comprehend, and we are also interested in risk perception in the specific context of agricultural drought adaptation.

4.3. Policy recommendations

Our results lead to several policy recommendations. First of all, we find a significant positive WTP for all types of the support program. The people in (agro-)pastoral communities are thus willing to participate and contribute to the support programmes. We demonstrate a clear heterogeneity in preferences for the type of support that is related to behavioural factors. This indicates the importance of considering human responses and heterogeneity in responses when designing drought risk adaptation policies. Below we discuss some examples of heterogeneity in preferences and how they can be used to target specific groups.

Firstly, we observe that all four types of support are preferred more by people with limited access to credit and savings than by people who have sufficient access to credit and savings. Adaptation support policies are thus likely to be more effective if they are targeted at households with limited financial resources. Alternatively, one could argue that the focus should be on increasing the availability of credit and promoting savings and saving groups, instead of the support types that are included in our experiment (Castells-Quintana et al., 2018). Especially because participants with better access to credit and savings also say to be significantly more likely to invest in all five out of the six adaptation measures that we included in our questionnaire. Increasing access to financial resources for poor households can be challenging. Kenya has the Hunger Safety Net Program that provides unconditional cash transfers for the most vulnerable households (Maione, 2020). These cash transfers are however mainly for fulfilling basic needs and will not be sufficient for households to start adaptation measures. Microfinancing could be a solution that can enable households to invest in climate change adaptation (Agrawala and Carraro, 2010; Castells-Quintana et al., 2018). Microfinancing can be beneficial for households that are willing to become entrepreneurs, but there are also examples of microfinancing schemes that are not effective and can actually increase poverty (Banerjee et al., 2015; Castells-Quintana et al., 2018; Van Rooyen et al., 2012). Another form of credit that is quite common in Sub-Saharan Africa is credit from Village Savings and Credit Associations (VSLAs). These informal village banking systems have shown to be an effective way to provide credit for small businesses, especially for women (Gichuki et al., 2014).

Secondly, we find that both people with a high intention to adapt and people with a positive attitude towards adaptation are likely to prefer a support program that includes a training, while people with a higher perceived self-efficacy are less likely to prefer training. Providing training and information thus seems to be especially relevant for people who would like to implement adaptation measures but are less confident about their own ability to do so. Several other studies also show that training and extension services provided by governments and NGOs are important drivers of adaptation decisions (Bryan et al., 2013; Di Falco et al., 2011; Wens et al., 2022). Many training initiatives by NGOs and governments already exist in the region, but a lack of knowledge is still an important barrier to adaptation.

Thirdly, people who observe adaptation in their social network are significantly less likely to prefer a subsidy and more likely to prefer training. Receiving little information about adaptation from the social network is often associated with living in remote areas with limited access to markets and access to information and extension services, and women often have less access to social networks that provide information about adaptation measures than men (Abid et al., 2017; Alare et al., 2022; Bedeke et al., 2019; Giroux et al., 2023; Otieno et al., 2021). Our results suggest that providing adaptation subsidies is more important for people who do not observe adaptation in their social network, while people who do observe adaptation in their social network are more likely to value training.

Fourthly, we find that people who expect a drought to occur very frequently mostly prefer to receive water supply and are less likely to select a support program with training. A possible explanation for this result is that at very high drought risk, adaptation limits are reached, and people might not believe in the effectiveness of adaptation measures anymore (Bubeck et al., 2018; Schrieks et al., 2023). Therefore, people with a very high-risk perception mainly value water supply and are less likely to choose a training to help them adapt. For the most vulnerable households, it is probably important to first make sure that they can fulfil basic needs before training and subsidies for adaptation can be provided. After that, it is important to start with promoting adaptation measures that are most useful under extreme drought conditions and that require relatively small adjustments to their existing way of life. Pastoralists who used to keeping cattle could, for example, start with switching to goats and camels which are livestock types that are more resistant to droughts (Opiyo et al., 2015).

5. Conclusion

To reduce vulnerability to future droughts, it is important that people in (agro-)pastoral communities implement household-level adaptation measures. Promotion of household-level adaptation is, therefore, included in climate change adaptation policies in many countries in sub-Saharan Africa. To develop effective adaptation policies, it is important to consider the needs of targeted communities and to understand to relationship between policies and adaptation behaviour. The aim of this study was, therefore, to identify preferences for different types of drought adaptation support in (agro-)pastoral communities, and how these preferences differ with individual perceptions and attitudes towards adaptation. Few studies exist that examine preferences for drought adaptation support in (agro-)pastoral communities, so our research contributes to this knowledge gap. Another novelty of our study is that we link the choice experiment data to survey data on three decision-making theories. By incorporating data on decision-making theories in our choice model, we bridge the gap between choice experiment studies and studies on adaptation behaviour, which can help to get a better understanding of the causal relationship between adaptation behaviour and preferences for adaptation support.

We observe clear heterogeneity in preferences for support related to behavioural factors from the different theories, this emphasises the benefit of explicitly embedding decision-making theories in the choice experiment analysis, which is currently rarely done in the choice experiment literature. Many participants have a strong preference for training, especially people with a high intention to adapt and a positive attitude towards adaptation seem to prefer a training. Training is, however, valued less by people who have a high self-efficacy, people with very high-risk perceptions, and people who do not observe adaptation in their social network. Providing training and information can thus be an effective way to increase the uptake of adaptation for people who are already positive towards adaptation but need some more knowledge to be able to implement measures. Households with a very high-risk perception and limited available resources might first need more fundamental support, such as water supply and emergency support before they can start thinking about implementing adaptation measures. We discussed various ways in which policymakers can consider these heterogeneities in preferences and human responses when designing and implementing adaptation policies. Future application of choice experiments on adaptation policy in different countries should also incorporate behavioural factors from established decision-making theories, to assess if the results of our study also hold in other contexts.

CRediT authorship contribution statement

Teun Schrieks: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **W.J. Wouter Botzen:** Writing – review & editing, Supervision, Conceptualization. **Toon Haer:** Writing – original draft, Supervision, Conceptualization. **Jeroen C.J.H. Aerts:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

Teun Schrieks reports financial support was provided by European Commission. Jeroen Aerts reports financial support was provided by European Commission. Toon Haer reports financial support was provided by the Dutch Research Council (NOW). If there are other authors, they 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

The data that has been used is confidential.

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Appendix A. Data collection

The data collection consisted of three phases. In the first phase, we have developed the initial survey and experiment based on literature study, expert knowledge and a scoping study in the research area performed by project partners from the DOWN2EARTH project. In the second phase (March 2022) we conducted sixteen focus group discussions in four villages in Isiolo County and 43 pre-test household survey interviews in two villages in Isiolo County. Based on the results of the focus group discussions and pre-tests, we designed the final survey and experiment. In the final phase (May 2022), the final survey with experiment has been conducted by ten local enumerators who were recruited by a local NGO. To make sure that all questions were clear and fully understood by the enumerators, this final phase started with two days of training and two days with 54 pilot interviews. The feedback from the pilot interviews was used to further improve the main survey, for which, 448 interviews were conducted which led to a total of 502 household interviews.

The risk aversion variables are based on a framed field experiment, integrated into the household survey (Schrieks et al., 2024). The experiment is a variation of the Holt and Laury (2002) multiple price list lottery experiment. Instead of abstract lotteries, we framed our experiment as a farming choice under varying rainfall conditions. We build on various previous studies with similar experiments in rural areas in low- and middle-income countries (e.g., de Brauw & Eozenou, 2014; Holden and Quiggin, 2017; Liu, 2013; Tanaka et al., 2010). Since we have both livestock farmers and some crop farmers, participants either received an experiment framed as a livestock or a crop decision. Probabilities in this experiment were framed as rainfall scenario with a probability of p for a bad rainy season and 1-p for a good rainy season (De Brauw and Eozenou, 2014). In the crop version, we asked participants to make a choice between two varieties of maize crops that they can plant on one acre of land. Variety A is a safe choice that will yield 20 bags of maize (50 kg per bag) in a rainy season with normal rains and a slightly lower yield of 16 bags in a bad rainy season with *little rainfall. Variety B is a riskier choice, with a much* higher yield of 36 bags in a good rainy season, but a low yield of only 2 bags in a bad rainy season. In the livestock version, participants had to choose the number of cows that they would like to hold. They again have two options. In option A (safe choice) they will get 10 cows. All cows will survive if there is a good rainy season. In a bad rainy season, there will be less water and pasture available, so only 8 of the 10 cows will survive. In option B (risky choice) they will get 18 cows, who will all survive a good rainy season, but only 1 cow will survive the bad rainy season. Each participant received 9 choices in which options A and B stayed the same, but probabilities varied from $p = 0.9$ to $p = 0.1$. Risk aversion levels are calculated based on the switching points (at which point do people switch from option A to B), following Tanaka et al. (2010) and Liu (2013).

Appendix B. Additional analyses

B.1. Data analysis on investment in adaptation measures

At the end of the choice experiment, we asked participants to imagine that they would receive the support program that they selected in the final choice card (choice card 4). Subsequently, we asked them to state for each of the six adaptation measures that they could spend the subsidy on (beekeeping, drought-resistant crops, kitchen garden, poultry farming, livestock insurance and rainwater harvesting), how likely it would be that they would invest in this measure after receiving the support. The answers are given on a five-point Likert scale from (1) "very unlikely" to (5) "very likely". We use these questions to analyse the relationship between the type of support that people receive and the intended investment in adaptation measures. Table B1 provides descriptive statistics for the answers to this question. For all six adaptation measures, the mean answer is between "likely" (4) and "very likely" (5), people thus state that they are eager to invest in all six adaptation measures if they receive the support. The most popular investments are in kitchen gardens and rainwater harvesting, and the least popular are beekeeping and livestock insurance. For livestock insurance, we also observe a significantly lower number of answers ($N = 448$) than for the other five adaptation measures. Not everyone is probably familiar with the concept of livestock insurance, therefore more people have answered "don't know" or did not answer.

Table B1
How likely do you think it is that you will invest in the following adaptation strategies?

	Mean	S.D.	N
Beekeeping	4.19	1.14	489
Drought-resistant crops	4.27	0.95	491
Kitchen garden	4.48	0.82	493
Poultry farming	4.37	1.00	492
Livestock insurance	4.11	1.17	448
Rainwater harvesting	4.46	0.85	491

The Likert scale questions for the six adaptation measure in Table B1 are used as dependent variables in six ordered logit models (McCullagh, 1980), so one model is estimated for each adaptation measure. As independent variables, we use the support that people would receive in the support program that they selected in the final choice card. For example, if a respondent selected a choice program in the final choice card that includes 10 jerry cans of water, 5 units of emergency livestock fodder, 10,000 KSH subsidy and no training, then these are the values of these independent variables for this respondent. Furthermore, we included control variables for location (Burat Ward or Oldonyiro Ward), access to credit and savings, and a dummy indicating if respondents have already implemented the specific adaptation measure.

In Table B2, we present the results of ordered logit regression models with as dependent variables the answers to the question on the investment in the adaptation measures, and as independent variables the attributes of the support program that they chose in the final choice card. Furthermore, as control variables, we add a dummy for Ward (1 = Burat Ward and 0 = Oldonyiro Ward), a composite variable for access to credit and savings, and dummy variables for if the household has already implemented the specific adaptation measure.[6] We find significant effects for the choice experiment

[6] We also estimated to models with, among others, control variables for age, gender, main livelihood activities and access to government support, but these variables did not improve the AIC scores, which is why we did not include them in the paper.

attributes in three out of the six models. After selecting a support program with high levels of emergency fodder supply and a high subsidy, participants state to be significantly more likely to invest in beekeeping, livestock insurance and rainwater harvesting. After selecting a support program with more water supply, participants state to be significantly less likely to invest in livestock insurance and rainwater harvesting and after selecting a program with a training, people state to be significantly less likely to invest in rainwater harvesting. Furthermore, we observe significant differences between Burat and Oldonyiro Ward. Participants in Burat Ward prefer investments in drought-resistant crops and kitchen gardens, while people in Oldonyiro Ward are more likely to invest in the other four measures. We find a significant positive effect of *access to credit and savings* in all models except for the *rainwater harvesting* model, in which this effect is not significant. Finally, people who have already implemented beekeeping would like to invest in more beekeeping equipment, while people who have already implemented rainwater harvesting are less likely to invest more in rainwater harvesting.

Table B2
Ordered logit models for investment in adaptation measures.

	Beekeeping	Drought-resistant crops	Kitchen garden	Livestock insurance	Poultry farming	Rainwater harvesting
Water	−0.122	0.669	−0.0720	−0.137*	0.531	−0.174**
	(0.0807)	(26.39)	(0.0915)	(0.0820)	(20.94)	(0.0817)
Fodder	0.237**	−0.973	0.0925	0.231**	−0.817	0.226**
	(0.111)	(39.58)	(0.128)	(0.113)	(31.40)	(0.112)
Subsidy	0.146**	−0.644	0.0818	0.148**	−0.558	0.161**
	(0.0742)	(26.39)	(0.0852)	(0.0750)	(20.94)	(0.0745)
Training	−0.830	5.025	−0.596	−0.819	4.097	−1.663***
	(0.627)	(197.9)	(0.707)	(0.636)	(157.0)	(0.638)
Burat Ward	−0.992***	0.403**	0.516***	−1.135***	−0.377**	−0.966***
	(0.207)	(0.187)	(0.190)	(0.200)	(0.192)	(0.197)
Access to credit and savings	0.395***	0.301***	0.493***	0.405***	0.508***	0.201
	(0.121)	(0.116)	(0.124)	(0.120)	(0.125)	(0.126)
Dummies for adaptation measure already implemented:						
Beekeeping	0.975***					
	(0.316)					
Drought-resistant crops		−0.465				
		(0.316)				
Kitchen garden			0.0471			
			(0.263)			
Livestock or crop insurance				0.117		
				(0.472)		
Poultry farming					0.0225	
					(0.203)	
Rainwater harvesting						−0.868***
						(0.253)
1|2	0.675	−15.67	−1.227	0.467	−14.00	−1.720
	(1.498)	(527.7)	(1.714)	(1.483)	(418.7)	(1.512)
2|3	1.646	−14.36	−0.402	1.421	−12.79	−0.674
	(1.490)	(527.7)	(1.698)	(1.484)	(418.7)	(1.487)
3|4	2.148	−13.77	−0.0294	1.984	−12.65	−0.126
	(1.490)	(527.7)	(1.694)	(1.487)	(418.7)	(1.486)
4|5	3.637**	−11.84	2.331	3.471**	−10.89	2.026
	(1.498)	(527.7)	(1.697)	(1.493)	(418.7)	(1.493)
N	488	490	492	447	491	490
AIC	1119.0	1098.8	889.9	1091.7	976.9	910.2

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

B.2. Alternative models

Table B3
Mixed logit model with, a) all parameters following a random normal distribution, b) monthly fee fixed and other parameters random, 3) correlated coefficients and fixed monthly fee.

	Mondel B1: All random	Mondel B2: Monthly fee fixed	Model B3: Monthly fee fixed, correlated coefficients
	Coefficient (Rob. SE)	Coefficient (Rob. SE)	Coefficient (Rob. SE)
Monthly fee (fixed)	–	−0.057*** (0.011)	−0.049*** (0.013)
Mean random parameters			
Water	0.118*** (0.014)	0.117*** (0.014)	0.125*** (0.016)
Fodder	0.038*** (0.009)	0.038*** (0.009)	0.039*** (0.009)
Subsidy	0.027*** (0.006)	0.027*** (0.005)	0.032*** (0.006)
Training	1.172*** (0.134)	1.153*** (0.130)	1.175*** (0.141)
Monthly fee	−0.057*** (0.012)	–	–
ASC opt-out	−26.958*** (10.806)	−31.670** (13.850)	−33.270*** (10.134)

(*continued on next page*)

Table B3 (*continued*)

	Mondel B1: All random	Mondel B2: Monthly fee fixed	Model B3: Monthly fee fixed, correlated coefficients
Standard deviations random parameters			
Water	0.161*** (0.019)	0.158*** (0.018)	0.164*** (0.035)
Fodder	−0.057*** (0.015)	−0.054*** (0.015)	0.039** (0.019)
Subsidy	0.031*** (0.011)	0.028** (0.012)	0.007 (0.011)
Training	−1.308*** (0.162)	−1.290*** (0.159)	−0.472 (0.375)
Monthly fee	0.007 (0.031)		–
ASC opt-out	11.816*** (4.377)	−13.653** (5.343)	−15.422*** (4.100)
N	502	502	502
Observations	2004	2004	2004
Log likelihood	−1207.18	−1208.36	−1195.79
AIC	2438.35	2438.72	2433.58
Adjusted ρ^2	0.4462	0.4462	0.4473
Number of draws	2000	2000	2000

* $p < 0.1$, **$p < 0.05$, ***$p < 0.01$ (one-sided p-values for monthly fee coefficient and means for random parameters and interaction effects, two-sided for standard deviations).

B.3. Household heads

Only 71 % of our respondents are the head of the household, so we also included 29 % of people who are not the head of their household. The reason that we also include people that are not household heads is that we wanted to get a representative representation of woman and of the different age groups. In the focus group discussion that we did in preparation of our data collection, we found out that adaptation decisions are often not made by only one person in the household. In the (agro-)pastoral communities, it is common that the men are away with the cattle and the women stay behind with the children. The men that are responsible for adaptation decisions related to the cattle, but women take all kinds of other adaptation decisions related to, among others, crop farming and water harvesting. Including only the male household heads would thus likely mean that we would miss information on important adaptation decisions that are taken by other members of the household. It is however likely that some decisions are mostly taken by the household head, especially if larger amounts of money are involved. To control for this, we did another run of the general preference space model including interaction effect of household head with all the experiment attributes (Table B4, Model B4). The only significant effect for household head is the interaction with the monthly fee attribute, for the four support attributes (water, fodder, subsidy and training) we do not find a significant effect for household head. We thus do not find evidence that household heads have a significantly different preference for the support types. We only find that household heads are slightly less sensitive for the monthly fee. The monthly fee coefficient for respondent who are not the household head is −0.083 and for household heads it is – 0.046 (−0.083 + 0.037), meaning that an increase in the monthly fee by 100 Kenyan Shilling will decrease the probability that someone who is not the head will select that support program by on average 0.083, while it only decreases the probability by 0.046 for household heads. Adding the household head interaction effects to the model does not lead to a significant change in the AIC score, meaning that it does not improve the model fit.

Table B4
Preference space mix logit model with household head interaction effects.

	Model B4: Household Head (HH)	
Fixed parameters	Coefficient (Rob. S.E.)	
Monthly fee base	−0.083*** (0.018)	
Monthly fee * HH	0.037** (0.022)	
Random parameters	Mean (Rob. S.E.)	S.D. (Rob. S.E.)
Water	0.118*** (0.015)	0.176*** (0.033)
Fodder	0.039*** (0.009)	−0.046 (0.030)
Subsidy	0.027** (0.006)	0.017 (0.019)
Training	1.182*** (0.135)	−0.930*** (0.275)
ASC	−25.153** (15.017)	−11.037* (6.238)
Interaction with household head (HH)		
Water *HH	−0.125 (0.201)	
Fodder * HH	0.357 (0.983)	
Subsidy* HH	1.284 (0.309)	
Training *HH	0.605 (0.108)	
N	502	
Observations	2004	
Log likelihood	−1203.13	
AIC	2438.26	
Adjusted ρ^2	0.4463	
Number of draws	2000	

* $p < 0.1$, **$p < 0.05$, ***$p < 0.01$ (one-sided p-values for monthly fee coefficient and means for random parameters, two-sided for standard deviations).

B.4. Livestock keepers and crop farmers

To analyses the effect of crop farming and livestock keeping on the preferences for supplementary livestock feeds, we have done an additional model analysis in which we have included dummy variables for crop farming and livestock breeding. Table B5 shows the results of this analysis. Both variables do not have significant interaction effects, and it does not lead to a significant improvement in model fit.

Table B5
Interaction effects with livestock keeping and crop farming.

	Model B5: Livestock keeping and crop farming	
Fixed parameters	Coefficient (Rob. S.E.)	
Monthly fee base	−0.057*** (0.011)	
Random parameters	Mean (Rob. S.E.)	S.D. (Rob. S.E.)
Water	0.116*** (0.016)	0.178*** (0.033)
Fodder	0.037*** (0.008)	−0.004 (0.012)
Subsidy	0.027** (0.006)	−0.028** (0.012)
Training	1.167*** (0.132)	−1.304*** (0.161)
ASC	−29.032** (11.060)	−13.299*** (4.476)
Interaction with livestock keeping (LK)		
Water *LK	−0.157 (0.174)	
Fodder * LK	16.572 (50.363)	
Interaction with crop farming (CF)		
Water* CF	0.030 (0.278)	
Fodder*CF	−8.095 (23.864)	
N	502	
Observations	2004	
Log likelihood	−1205.38	
AIC	2440.75	
Adjusted ρ^2	0.4457	
Number of draws	2000	

B.5. Climate scenarios

For half of the respondents in our choices we asked them to imagine that 4 out of the coming 10 rainy seasons are expected to fail (climate scenario 1) and for the other half we said that 8 out of the coming 10 rainy seasons are expected to fail (climate scenario 2). In Model B6 (Table B6), we analyse the differences in choices between these two groups by adding a dummy variable (S2) which is one if people received scenario 2 and zero for people who received scenario one. Table B6 shows that there are no significant differences between these two groups. Furthermore, controlling for the climate scenarios does not improve the model fit (higher AIC and lower Adjusted ρ^2 than in model 1). This could mean that the drought frequency does not affect the preferences for support, but we think that is unlikely because we do find that people's expected frequency of drought has a significant effect on their choices. Another explanation could be that we made a mistake in the experiment design. The drought scenarios were first presented to the respondents and only after that we explained the choice experiment. We think it is likely that the respondents received too much information and therefore did not think about the drought scenarios anymore when they made their choices. It is also possible that it was too difficult to imagine the drought scenarios and that people are just making choices based on what they have been experiencing. We do not have the data to test these hypotheses, but future research could further analyse the role of expected drought scenarios in preferences for adaptation support.

Table B6
Climate scenarios.

	Model B6: Climate Scenarios	
Fixed parameters	Coefficient (Rob. S.E.)	
Monthly fee base	−0.077*** (0.017)	
Monthly fee * S2	0.035 (0.023)	
Random parameters	Mean (Rob. S.E.)	S.D. (Rob. S.E.)
Water	0.132*** (0.020)	0.176*** (0.026)
Fodder	0.034*** (0.011)	0.051*** (0.015)
Subsidy	0.026*** (0.008)	0.031*** (0.011)
Training	1.211*** (0.179)	−1.356*** (0.191)
ASC	−49.241* (25.465)	−20.955** (10.279)
Interaction with climate scenario S2		
Water *S2	−0.161 (0.171)	
Fodder * S2	0.329 (0.519)	
Subsidy* S2	0.094 (0.451)	
Training *S2	−0.033 (0.212)	
N	502	
Observations	2004	
Log likelihood	−1204.94	
AIC	2441.89	
Adjusted ρ^2	0.4454	
Number of draws	2000	

* $p < 0.1$, **$p < 0.05$, ***$p < 0.01$ (two-sided p-values).

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