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ORIGINAL ARTICLE

Assessing key behavioural theories of drought risk adaptation: Evidence from rural Kenya

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Abstract
The Horn of Africa Drylands are increasingly experiencing severe droughts, which impose a threat on traditional livelihood strategies. Understanding adaptation behavior in rural communities is key to helping reduce the impact of these droughts. We investigate adaptation behavior by assessing four established economic and social psychological theories on decision making under risk: expected utility theory (EUT), rank dependent utility theory (RDU), protection motivation theory (PMT), and theory of planned behavior (PMT). To measure adaptation behavior and the theory constructs, we conducted a household survey in Kenya ($N = 502$). Regression analysis shows that the economic theories (EUT and RDU) have the best fit for our data. Risk and time preferences are found to play an important role in adaptation decisions. An analysis of differences in decision making for distinct types of adaptation measures shows that risk averse (agro-)pastoralists are more likely to implement adaptation measures that are adjustments to their current livelihood practices, and less willing to invest in adaptation measures that require a shift to other livelihood activities. Moreover, we find significant effects for elements of the social psychological theories (PMT and TPB). A person's belief in their own ability to implement an adaptation measure (perceived self-efficacy) and adaptation by family and friends are important factors in explaining adaptation decisions. Finally, we find that the type of adaptation measures that people implement is influenced by, among others, gender, education level, access to financial resources, and access to government support or aid. Our analysis gives insights into the drivers of individual adaptation decisions, which can enhance policies promoting adaptation of dryland communities.

KEYWORDS
adaptation behavior, behavioral theories, drought risk, Kenya, risk perceptions

1 | INTRODUCTION

People in rural African drylands have been living as pastoralists or agro-pastoralists for millennia and have developed a range of coping strategies to deal with rainfall variability and frequent droughts (United Nations Convention to Combat Desertification [UNCCD], United Nations Development Programme [UNDP], & United Nations Environment Programme [UNEP], 2009). Changes in socio-economic and political circumstances combined with increases in human and livestock populations have, however, increased the pressure on the dryland's natural resources (King et al., 2018; UNCCD et al., 2009). The pressure on the rangelands and (agro-)pastoral communities is amplified by climate change which causes an increased frequency and severity of droughts (Ng'ang'a & Crane, 2020; UNCCD et al., 2009). Traditional coping strategies are not enough to deal with these combined threats on the livelihoods of (agro-)pastoral communities. New adaptation strategies are, therefore, required to deal with the impacts of climate change. To develop these adaptation strategies, it is important to better understand the drivers and barriers of current drought adaptation decisions.

In this study, we use household survey data to study adaptation behavior in (agro-)pastoral communities in Isiolo

County, Kenya. To provide theoretically sound insights into adaptive behavior, empirical research needs to be grounded in psychological or economic decision-making theories, which also helps to get a better understanding of the causal links between risk and the adaptation decision-making process (Kuhlicke et al., 2023; Waldman et al., 2020). However, empirical research into the use of decision theories in the field of disaster risk reduction and climate change adaptation is rather fragmented, and more empirical knowledge is needed on what factors shape adaptation and vulnerability to risk (Rufat et al., 2022). Economists and psychologists who study adaptation behavior take different perspectives which can sometimes lead to contradicting results, but there is also quite some overlap between the theories from the two disciplines (Schrieks et al., 2021; Waldman et al., 2020). We combine insights from both disciplines by developing a household survey that is grounded in both economic and social psychological decision-making theories. Based on recommendations by Schrieks et al. (2021) we include four theories: two social psychological theories — protection motivation theory (PMT) and the theory of planned behavior (TPB) — and two economic theories — expected utility theory (EUT) and rank dependent utility theory (RDU). These selected theories are commonly used to analyze risk-reducing behavior, but their application for explaining drought adaptation is rarely systematically assessed. The aim of the article is therefore twofold: (1) By assessing four different theories, we aim to get a better understanding of their relevance in the context of drought risk adaptation, and by doing so, (2) we improve our knowledge on decision making in (agro-) pastoral communities, to inform drought risk adaptation policy.

PMT and TPB assess the relationship between the intention to adapt and different types of perceptions and attitudes toward adaptation and have often been used to model farmers' intentions to adapt to drought or other climate-related hazards (Arunrat et al., 2017; Delfiyan et al., 2021; Gebrehiwot & Van der Veen, 2021; Keshavarz & Karami, 2016; Van Duinen et al., 2015; Van Valkengoed et al., 2023). Most existing studies measure perceptions toward adaptation as aggregated variables related to adaptation in general and do not make a distinction between perceptions for different types of adaptation measures. Intention to adapt is usually also measured as one aggregated variable representing adaptation behavior in general, which does not capture differences in preferences for distinct adaptation measures (e.g., Arunrat et al., 2017; Delfiyan et al., 2021; Gebrehiwot & van der Veen, 2021; Van Duinen et al., 2015). Some studies, therefore, run separate regression models for individual adaptation measures (e.g., Truelove et al., 2015; Van Valkengoed et al., 2023), which enables measuring differences in drivers for distinct measures but does not account for relationships between different adaptation actions (Noll et al., 2022). Two recent studies on flood risk adaptation behavior, therefore, separately measure the factors of PMT for individual adaptation measures which allows to not only account for differences in preferences between households, but also differences in preferences for distinct types of adaptation measures within households (Jansen et al., 2021; Noll et al., 2022). We build on this method by also measuring the PMT variables, and one TPB variable, for each measure separately and extending their method to the drought context. We estimate several different regression models, both with aggregated and nonaggregated variables, to analyze which method best explains adaptation behavior in our context, and to contribute to the academic discussion on the measurement of adaptation behavior.

Another novelty of this article is that we combine the analysis of PMT and TPB with two often-used theories in economics (EUT and RDU). By combining these theories in one paper, we aim to bridge the gap between the disciplines and assess the complementarity of the theories. The main factor in EUT and RDU that is driving adaptation behavior, and is not included in the psychological theories, is risk aversion. Several studies find positive relations between risk aversion and implementation of some types of adaptation measures (e.g., Asravor, 2019; Holden & Quiggin, 2017; Jin et al., 2016; Ward & Singh, 2015), but studies also find the opposite effect for other types of adaptation measures (Asravor, 2019; Brick & Visser, 2015; Jin et al., 2016; Liu, 2013). Besides assessing the effect of risk aversion on adaptation behavior in general, we also assess the differences in the effect of risk aversion on distinct types of adaptation measures, for which we estimate separate regression models for individual adaptation measures. In these models, we also analyze the relation between the type of adaptation measures that people select and socioeconomic and demographic variables, such as gender, livelihood activity, access to financial resources, and access to government support or aid. Based on the regression results we provide policy recommendations for policymakers that aim to promote specific types of adaptation measures.

In the next section, we start with a description of the four theories combined with the hypotheses that follow from the theories, followed by a description of the data collection and the data analysis. In section 3 we present the results and section 4 follows with the discussion and conclusion.

2 | METHODS

2.1 | Theories and hypotheses: Key drivers and barriers

Figure 1 gives an overview of four behavioral theories commonly used in studies on adaptive action. The right side of the figure shows the expected utility theory (EUT) and rank dependent utility theory (RDU). These theories assume that people select the adaptation options that give them the highest expected utility, which depends on the expected costs and benefits, risk perceptions, risk attitudes, and time preferences (Diecidue & Wakker, 2001; Machina, 2008; Quiggin, 1982; Von Neumann & Morgenstern, 1947). The left side of Figure 1 shows the TPB, which argues that the intention to adapt depends on someone's attitude toward adaptation, the influences of subjective norms, and the perceived behavioural

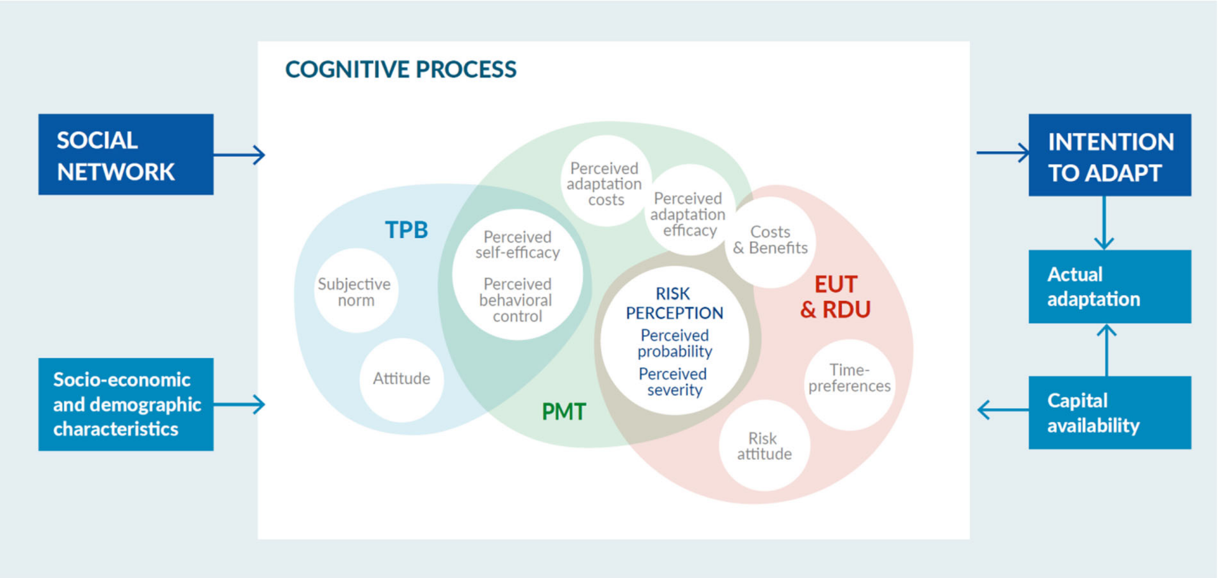

FIGURE 1 Overview of drivers for drought adaptation according to different decision-making theories. Based on fig. 1 in Schrieks et al. (2021).

control (Ajzen, 1991, 2002; Arunrat et al., 2017; Yazdanpanah Hayati et al., 2014). The PMT comes in between those theories. PMT models the intention to adapt as a function of risk appraisal and coping appraisal (Maddux & Rogers, 1983; Rogers, 1983). The risk appraisal is a function of the perceived probability and perceived severity of a drought event. The coping appraisal consists of three elements: perceived adaptation costs, perceived adaptation efficacy, and perceived self-efficacy. Below we discuss all elements of the theories, based on these theory elements we formulate the hypotheses that we will test in our regression analyses, followed by an overview of all hypotheses in Table 1.

The economic theories, model decision making as a maximization process. People are assumed to evaluate the available options and select the option that gives them the highest expected utility. Furthermore, EUT and RDU distinguish themselves from the psychological theories (PMT and TPB) with the inclusion of risk attitudes. People are generally found to be risk averse which means that they prefer a safe choice over a risky choice with the same expected outcome (Bombardini & Trebbi, 2012; Jin et al., 2016). To measure people's level of risk aversion, we conducted a lab-in-the-field experiment (see section 2.2). In this experiment, individuals had to make a choice between two lotteries (A or B) that were framed as two farming alternatives. Both alternatives have two possible outcomes depending on the rainfall. For the EUT model, we assumed that people (implicitly) use the constant relative risk aversion (CRRA) utility function in Equation 1 to calculate the expected utility of each outcome and that they select the alternative that gives them the highest expected utility. The constant relative risk aversion utility function is the most common type of utility function and is often found to give a better fit than other types of functions (Wakker, 2008). Formally, the generic form of the function of utility U_i over outcome x_i is: $U_i = x_i^{(1-\beta)}$. In our application, the expected utility of alternative j (lottery A or lottery B) is a function of its outcome in a good rainy season ($x_{G,j}$) that occurs with probability p_G, its outcome in the bad rainy season ($x_{B,j}$) that occurs with probability $1 - p_G$, and the utility curvature parameter β. The utility curvature parameter β represents the level of risk aversion, individuals are risk averse if $\beta > 0$, risk neutral if $\beta = 0$, and risk seeking if $\beta < 0$.[1]

$$\mathrm{EU}_j = p_G\, x_{G,j}^{(1-\beta)} + \left(1 - p_G\right) x_{B,j}^{(1-\beta)} \tag{1}$$

EUT assumes that people process probabilities linearly, which is argued not to reflect reality (Kahneman & Tversky, 1979; Prelec, 1998). RDU is a variation of expected utility that makes a generalization of this assumption by allowing for nonlinear weighting of probabilities (Diecidue & Wakker, 2001; Quiggin, 1982). To model RDU we use the same CRRA utility function, but we add a probability weighting function ($w(p_i)$) based on Tversky and Kahneman (1992):

$$\mathrm{RDU}_j = W(p_G)\, x_{G,j}^{(1-\beta)} + W(p_B)\, x_{B,j}^{(1-\beta)} \tag{2}$$

$$w\left(p_G\right) = \frac{p_G^{\gamma}}{{p_G^{\gamma} + \left(1 - p_G\right)^{\gamma}}^{1/\gamma}} \tag{3}$$

$$w(p_B) = 1 - w\left(p_G\right) \tag{4}$$

[1] The standard CRRA (or power) utility function, as used in Wakker (2008), is $U_i = x_i^{\beta}$. We rewrite this formula to $U_i = x_i^{(1-\beta)}$, for ease of understanding the effect of risk aversion (in a way that a high coefficient means high risk-aversion), and to be able to compare our results with the often used CRRA risk aversion function for EUT, which is $U_i = \frac{x_i^{(1-\beta)}}{1-\beta}$ (Liu, 2013).

TABLE 1 Hypotheses.

Theory constructs	Hypotheses	Theories
Risk attitudes	H1a: In the EUT model, the risk aversion parameter (β) is positively related with adaptation.	EUT & RDU
	H1b: In the RDU model, the utility curvature parameter (β) is positively related with adaptation.	
	H1c: In the RDU model, the probability weighting parameter (γ) is positively related with adaptation.	
	H1d: Risk aversion is positively related with implementation of low-risk adaptation measures, but negatively related with implementation of high-risk adaptation measures or measures that the households are unfamiliar with.	
Time preferences	H2: A higher valuation of the future is positively related with adaptation.	EUT & RDU
Risk perceptions	H3: Risk perceptions are positively related with adaptation.	EUT, RDU, & PMT
Perceived adaptation efficacy/ Benefits	H4a: Perceived adaptation efficacy (or benefits) is positively related with the intention to adapt.	EUT, RDU, & PMT
Perceived adaptation costs	H4b: Perceived adaptation costs are negatively related with the intention to adapt.	EUT, RDU, & PMT
Perceived self-efficacy/ Perceived behavioural control	H5a: Perceived self-efficacy (PMT) or perceived behavioural control (TPB) is positively related with the intention to adapt.	PMT & TPB
Attitudes	H5b: Positive attitudes toward adaptation are positively related with the intention to adapt.	TPB
Subjective norm	H5c: A social network that is positive toward adaptation is positively related with the intention to adapt.	TPB
Capital availability / household budget	H6: The household budget is positively related with adaptation.	EUT, RDU, PMT (& TPB)

The weight of the probability for the high payoff outcome is $w(p_G)$ and the weight for the probability of the low payoff outcome is $w(p_B)$. The parameter γ is the probability weighting coefficient. With $\gamma = 1$ the RDU function collapses to the EUT function, $\gamma < 1$ means that people overweight small probabilities and underweight large probabilities, $\gamma > 1$ means that people underweight small probabilities and overweight larger probabilities.

Since adaptation is supposed to reduce risk, we expect that a higher level of risk aversion is related to more adaptation. This means that we expect to find a positive correlation between β and adaptation behavior in the EUT model (**H1a**). The level of risk aversion in the RDU model depends on both the utility curvature parameter β, and the probability weighting parameter γ. For β the effect is the same as in EUT, a larger β means a higher level of risk aversion (**H1b**), but for γ it depends on the risk context. In our study, we are looking at drought risk in Kenya. The probability of drought is very high in this region (World Food Programme [WFP], 2023), thus we are considering large risk probabilities. A small γ means that people underweight large probabilities, while a large γ means that people overweight large probabilities. We therefore expect that larger γ is related to more adaptation (**H1c**).

In theory, adaptation should reduce drought risk, but that is not always clear for all types of adaptation measures. Several studies find positive relations between risk aversion and implementation of some types of adaptation measures (Asravor, 2019; Holden & Quiggin, 2017; Jin et al., 2016; Ward & Singh, 2015), but studies also find the opposite effect for other types of adaptation measures (Asravor, 2019; Brick & Visser, 2015; Jin et al., 2016; Liu, 2013). The results of these studies indicate that risk averse farmers are more likely to adopt low-risk adaptation strategies but less likely to invest in risky new techniques that they are not familiar with (**H1d**).

The second element in EUT and RDU is time preferences. People put a higher value on current wealth than on future wealth, future costs and benefits are therefore discounted (Frederick et al., 2002). An investment in an adaptation decision is a cost that is expected to generate benefits in the future. The expectation is, therefore, that people who put more weight on the future are more likely to implement adaptation measures (**H2**).

Furthermore, subjective risk perceptions are included in the EUT and RDU models,[2] which are also part of the PMT. Risk perceptions in PMT are represented in the risk appraisal, which is subdivided into two elements: the perceived probability and the perceived severity. In the context of drought risk, perceived probability is the expectation of the probability that one is exposed to a drought and perceived severity is the expectation of the severity of the impact if the drought

[2] Traditional EUT assumes that people have perfect information about the risks (Von Neumann & Morgenstern, 1947). In reality, there is uncertainty about the risk and different people perceive the risk in a different way. Most economic studies therefore apply a subjective version of EUT and RDU, which assumes that risk perceptions are determined by both objective and subjective factors (Fishburn, 1981; Savage, 1954).

occurs (Keshavarz & Karami, 2016). People with higher risk perceptions are expected to implement more adaptation measures (**H3**).

Besides risk attitudes and risk perceptions, the main factors in the EUT and RDU model are the costs and benefits. They are very similar to the perceived adaptation efficacy and perceived adaptation costs that are part of the PMT. We therefore include perceived adaptation efficacy and perceived adaptation costs in the EUT, RDU, and PMT models. We expect a positive relation between perceived adaptation efficacy (or benefits) and adaptation (**H4a**) and a negative relation between perceived costs and adaptation (**H4b**)

The final element of PMT, which is not included in EUT and RDU, is perceived self-efficacy. This is one's belief in their own ability to implement an adaptation measure, which is (almost) the same as perceived behavioural control in TPB (Arunrat et al., 2017; Schrieks et al., 2021; Yazdanpanah et al., 2014). A higher perceived self-efficacy (PMT) or perceived behavioural control (TPB) is expected to result in a higher intention to adapt (**H5a**).

Besides perceived behavioral control, TPB adds two other psychological factors — attitude and subjective norm — that are not part of the other three theories (Ajzen, 1991, 2002). In the context of drought adaptation, attitudes are the personal beliefs about the importance and usefulness of an adaptation measure, and subjective norms reflect the influence of the social network on performing the behavior (Arunrat et al., 2017; Schrieks et al., 2021; Yazdanpanah et al., 2014). We expect that a positive attitude toward adaptation and a social network that is positive toward adaptation both lead to a higher intention to adapt (**H5b** and **H5c**).

The last hypothesis that we want to test is related to the household budget or capital availability, which is directly included in EUT & RDU as part of the budget constraint, and indirectly in PMT since it influences perceived costs and perceived self-efficacy. In TPB, the household budget is not directly part of the intention, but the actual behavior depends on both the intention and the actual control which includes the availability of required resources and skills (Ajzen, 1991). People are only able to adapt if this is within their financial capabilities, we therefore expect a positive relation between household budget and adaptation (**H6**).

2.2 | Data collection

We conducted a household survey with 502 respondents from (agro-)pastoral communities in Oldonyiro ward and Burat ward in Isiolo County, Kenya (Figure 2). The county has low and irregular rainfall, strongly concentrated in two rainy seasons: the short rains (MAM) in March, April, and May and long rains (OND) in October, November, and December (Government of Kenya [GoK], 2018; Quandt & Kimathi, 2017). Due to the high seasonality of rainfall, failure of these rainy seasons can be destructive to local communities. The majority of the land in Isiolo County (80%) is communally owned grazing land with pastoralism as the main livelihood activity and a bit of agro-pastoralism in the semi-arid zones (Ministry of Agriculture, Livestock and Fisheries, 2018).

We employed a stratified sampling method in which we divided the population into six subgroups based on gender and age categories (18–29, 30–49, and 50+), with data 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 to an underrepresentation of young men and an overrepresentation of women and older men.

In the questionnaire, we included questions on, among others, adaptation decisions, livelihood activities, drought risk perceptions, and household characteristics. To measure the current level of adaptation and the intention for future adaptation, we have asked each participant about 15 different types of adaptation measures (Table 2). We selected these 15 measures based on scoping studies and expert knowledge. For each measure, we first asked if their household already has implemented the measure or has contributed to the implementation of the measure by the community. The 'percentage implemented' in Table 2 thus represents the (self-reported) percentage of households in the survey that have already implemented the measure. Subsequently, we asked which measures they are planning to adopt in the coming 5 years. The 'percentage intended' in Table 2 gives the percentage of households that indicated that they intend to adopt the measure in the coming 5 years.

The survey included multiple questions for each element in the TPB and PMT, derived from previous studies (Arunrat et al., 2017; Gebrehiwot & Van der Veen, 2015; Grothmann & Patt, 2005; Keshavarz & Karami, 2016; Truelove et al., 2015; Van Duinen et al., 2015; Wang et al., 2019; Wens et al., 2021; Yazdanpanah et al., 2014). More information on the data collection can be found in the supporting Information S1.

To estimate the parameters of EUT and RDU, we have conducted a framed lab-in-the-field experiment, integrated into the household survey. 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 & Quiggin, 2017; Liu, 2013; Tanaka et al., 2010). These studies mainly focus on crop farmers, but our respondents also include many pastoralists. We therefore developed two different versions of the experiment: a crop version and a livestock version. Here we summarize the experiment, a full description, with participant instructions, can be found in Supporting Information S2.

In both the crop version and the livestock version, probabilities are framed as rainfall scenarios, with probability p for a bad rainy season and 1-p for a good rainy season (de Brauw & Eozenou, 2014). In the crop version, we asked participants

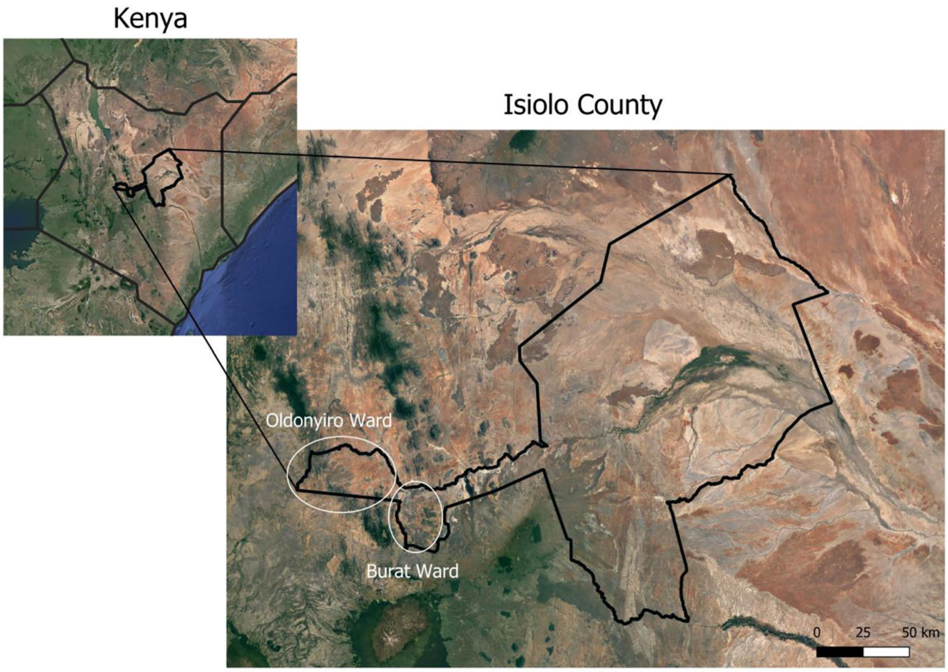

FIGURE 2 Location of the case study areas, Oldonyiro ward and Burat ward, in Isiolo county in Kenya.

TABLE 2 Overview of adaptation measures with percentages for households that have implemented the measure and intentions to implement the measure.

Label	Adaptation measure	Percentage implemented ($N = 502$)	Percentage intended ($N = 502$)
AF	Planting trees for agroforestry	9%	13%
BK	Beekeeping	17%	21%
BO	Digging a borehole or shallow well	3%	25%
DC	Planting drought-resistant crops	8%	16%
IN	Livestock or crop insurance	4%	14%
IR	Irrigation	5%	9%
KG	Starting a kitchen garden	15%	22%
LD	Changing and diversifying livestock species from grazers to browsers	33%	16%
MO	Moving further than normal with livestock	16%	1%
PC	Pasture conservation	19%	14%
PF	Poultry farming	29%	25%
RH	Rainwater harvesting	16%	25%
SG	Saving money by participating in a savings group	49%	23%
SB	Starting a small business	39%	37%
VA	Vaccination of livestock	9%	14%

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 two choice sets with nine choices. In the first set, options A and B stayed the same, but probabilities varied from $p = 0.9$ to $p = 0.1$. In the second set, we fixed the probabilities at $p = 0.5$, but we varied the payoffs for the good rainfall scenario.

To calculate the level of risk aversion, we plugged in the details of each choice in the formulas of section 2.1. For EUT we only used the choices in choice set one to calculate the utility curvature parameter. For RDU, we used the first choice set, with varying probabilities, to calculate the probability weighting parameter, and the second set, with fixed probabilities, to calculate the utility curvature parameter. For these calculations, we followed Tanaka et al (2010) and Liu (2013). Based on the switching points (when people switch from option A to option B) in the choice sets, we could calculate the range of β and γ that matches someone's choices. We took the midpoints of the ranges of β and γ as values for the utility curvature and probability weighting variables that are used in the regression analysis.

In the fixed probabilities part of our experiment, a large group of participants always selected the safe option. For these individuals, we do not have a switching point, which means that we can only estimate the lower bound of their utility curvature parameter, which is $\beta = 0.28$. Following Tanaka et al. (2010) and Liu (2013) we use this lower bound as the value for the utility curvature parameter, but this leads to an underestimation of the utility curvature parameter and an overestimation of the probability weighting parameter for this group (Supporting information S3). To deal with this issue, we created a dummy variable (*Risk averse)* for the group that always selected option A. In our regression analyses, we include the interaction effects of this dummy variable with both the utility curvature parameter and probability weighting parameter, to separate the effect of this risk averse group.

2.3 | Data analysis

We used linear and logistic regression models to analyze the drivers and barriers of drought adaptation decisions. The dependent variables of the regression models were the intention to adapt or past adaptation (Table 2).

We applied two different regression strategies to estimate the effect of the theory variables on the intention to adapt. In the first method, we disentangled the intention of all adaptation measures and included adaptation measure specific values for the coping appraisal variables, which allowed us to measure the within-person effects of the coping appraisal variables (perceived costs, perceived adaptation efficacy and perceived self-efficacy) on the intention to adapt (Jansen et al., 2021; Noll et al., 2022). The dependent variable is a binary variable for intention to adopt the adaptation measure (1 = yes, 0 = no). We split the data into 15 observations for each household (one observation for each adaptation measure) and used a logistic regression model with clustered standard errors (clustered on household ID). Since we are focusing on intentions, we excluded the observation if the household has already implemented the measure.

In the second method, we combined all adaptation measures into one aggregated measure for intention to adapt and we measured the coping appraisal variables for each household as the average values across adaptation measures. Similar to Noll et al. (2021), we used proportion intended as dependent variable, which measures the number of adaptation measures that the household is planning to implement as a proportion of adaptation measures that are still available for this household to implement:

$$\text{Proportion intended} = \frac{\#\ \text{Intended measures}}{15 - \#\ \text{Measures already implemented}} \tag{5}$$

We also estimated regression models with past adaptation as dependent variable, to control for a potential intention-behavior bias (Bubeck et al., 2020; Kesternich et al., 2022). Like the first method for intention, we ran a logistic regression model with clustered standard errors, but now with *Implemented (yes = 1, no = 0)* as dependent variable and we included all households. Finally, we estimated logistic regression models for each adaptation measure separately, which allows to analyze the differences for distinct types of adaptation measures.

The main independent regression variables are the variables that measure the parameters of the four theories. Table 3 gives an overview of the main variables with the coding and the corresponding theory. For each dependent variable, we estimated regression models for all four theories and a model where we combined the different theories and added control variables ('Mix model'). We analyzed which variables have significant effects on adaptation decisions and based on that we discuss which elements of the theories are the main drivers and barriers of adaptation. Finally, we compared the Akaike information criteria (AIC) to compare the performance of each model in explaining adaptation behavior (Cavanaugh & Neath, 2019). Comparing the AIC scores requires equal sample sizes. Therefore, we must impute missing data for some of the variables. The proportion of missing data is small, with a maximum of 5.6% for one variable (probability weighting) and well below the 5% for all other variables, which means that missing data are unlikely to create biases and that we can safely ignore the missing values or use simple imputation (Dong & Peng, 2013; Jakobsen et al., 2017). To be able to compare the AIC scores, we used simple median imputation in the regression tables in the results sections, but we also did a complete case analysis (deleting observations with missing values) which can be found in supporting Information S4. We did not find significant differences in the results between these two methods.

3 | RESULTS

3.1 | Intention to adapt

Table 4 gives the marginal effect from the logistic regression model with as dependent variable the binary variable for intention to adapt. We use clustered standard errors and adaptation measure specific values for the coping appraisal

TABLE 3 Main independent regression variables.

Theory construct	Variable name	Questions/Description	Coding	Theory
Risk attitude	Utility curvature	Utility curvature of the RDU function, β in Equation (2), based on switching point in the fixed probability part of the experiment.	Supporting information S3	RDU
Risk attitude	Probability weighting	Probability weighting of the RDU function, γ in Equation (3), based on switching point in the varying probability part of the experiment.	Supporting information S3	RDU
Risk attitude	Risk aversion EUT	Risk aversion in the EUT function, β in Equation (1), based on switching point in the varying probability part of the experiment.	Supporting information S3	EUT
Risk appraisal	Expected frequency	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"	PMT EUT RDU
Risk appraisal	Perceived relative 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"	PMT EUT RDU
Coping appraisal	Perceived self-efficacy	For each of the 15 adaptation measures we asked: To what extent do you feel able implementing the following measure that reduces the impact of drought on your household?	5-point Likert scale from "not able at all" to "very able"	PMT TPB
Coping appraisal	Perceived adaptation efficacy	For each of the 15 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?'	5-point Likert scale from "not effective at all" to "very effective"	PMT EUT RDU
Coping appraisal	Perceived adaptation costs	For each of the 15 adaptation measures we asked: How high do you think the total costs would be for you to carry out this adaptation measure, in terms of financial costs as well as time and effort?	5-point Likert scale from "not high at all' to "very high"	PMT EUT RDU
Attitude	Attitude	To what extent do you agree with the following statements? 1) Implementing drought adaptation measures in the next 5 years is important for me and my household. 2) Adaptation measures are useful for my household to apply in the next 5 years	5-point Likert scale from "strongly disagree" to "strongly agree" Average value of the two questions. (Cronbach's $\alpha = 0.873$)	TPB
Subjective norm	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 liker scale from "None" to "All of them"	TPB
Budget constraint	Yearly Expenditure	Sum of following four elements:Can you give us an estimate on your yearly expenditures on: 1. (crop) farming activities? 2. Livestock-related activities? 3. non-food items? 4. food?	Total yearly expenditures in 100,000 Kenyan Shillings (KSh)	EUT RDU PMT
Budget constraint	Access to credit	To what extent do you feel that you have sufficient access to the following resources to cope with droughts? Loans	5-point liker scale from "No access at all" to "More than sufficient access"	EUT RDU PMT
Budget constraint	Yearly savings	Do you use part of your income as savings for the future? If yes: Can you give an estimation of your yearly savings? 1) <10K, 2) 10K–20K, 3) 20K–30K, 4) 30K–40K, 5) >40K	0 if no savings, otherwise midpoint of the category. 45,000 KSh for > 40K	EUT RDU PMT
Time preferences	Time preferences	When it comes to financial decisions, how would you assess your willingness to give up something today in order to benefit from that in the future?	11-point Likert scale from "0: completely unwilling" to "10: very willing"	EUT RDU

[a]We included specific questions on subjective norm in our survey, but the correlation between the subjective norm and the attitude questions was too large, which created multicollinearity issues. We therefore used adaptation by family and friend as proxy for subjective norm instead of the questions about the subjective norms itself. See Supporting Information S1 for a pairwise correlation table for all variables in Table 3.

TABLE 4 Marginal effects for logistic regression models with clustered standard errors (clustered on household "ID") Dependent variable: Intention to adapt (0 = no, 1 = yes).

	EUT	RDU	PMT	TPB	Mix
Risk aversion (β EUT)	0.04***				
	(0.01)				
Expected frequency	−0.00	0.00	−0.02*		0.00
	(0.01)	(0.01)	(0.01)		(0.01)
Relative drought impact	0.00	0.00	0.00		0.01
	(0.01)	(0.01)	(0.01)		(0.01)
Perceived adaptation efficacy	0.06***	0.06***	0.05***		0.05***
	(0.01)	(0.01)	(0.01)		(0.01)
Perceived costs	−0.01*	−0.01**	−0.01		−0.00
	(0.01)	(0.01)	(0.01)		(0.01)
Time preferences	0.02***	0.02***			0.02***
	(0.00)	(0.00)			(0.00)
Yearly expenditure (in 100,000 KSh)	0.01	0.02	−0.00		−0.00
	(0.01)	(0.01)	(0.01)		(0.01)
Yearly savings (in 100,000 KSh)	0.14**	0.14**	0.13*		0.03
	(0.07)	(0.07)	(0.07)		(0.07)
Access to credit	0.01	0.02*	−0.01		−0.00
	(0.01)	(0.01)	(0.01)		(0.01)
Utility curvature (β RDU)		0.02			0.01
		(0.03)			(0.03)
Probability weighting (γ RDU)		0.02***			0.02***
		(0.00)			(0.00)
Perceived self-efficacy			0.02***	0.03***	0.04***
			(0.01)	(0.01)	(0.01)
Attitude				0.04***	0.01
				(0.01)	(0.01)
Adaptation by family and friends				0.03***	0.04***
				(0.01)	(0.01)
#Implemented measures					0.01**
					(0.01)
Livestock keeper					−0.03
					(0.02)
Household size					0.00*
					(0.00)
N	6,145.00	6,145.00	6,145.00	6,145.00	6,145.00
AIC	6231.03	6201.61	6370.21	6421.61	6062.74

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

variables. We will discuss the main results per theory starting with EUT and RDU, followed by PMT and TPB, and finally, a mix model in which we combine the four theories.

3.1.1 | EUT and RDU

The first variables for EUT and RDU are the variables that measure risk attitudes, which are based on the results of the lab-in-the-field experiment. In EUT, we find a significant positive effect for risk aversion, meaning that risk averse people have a higher intention to adapt (supporting H1a). In the RDU model, risk attitudes are measured with both utility curvature (β and probability weighting (γ).[3] The utility curvature parameter is not significant (no evidence for H1b). The

[3] As a robustness check, we also estimate the models with interaction effects with *Risk averse* a dummy variable for people who always selected option A in the fixed proba-

probability weighting variable has a significant positive effect (supporting H1c), which means that people who overweight large probabilities more, have a higher intention to adapt.

The two variables for risk perceptions (expected frequency and relative drought impact) are not significant in the EUT and RDU models (no evidence for H1d). Perceived adaptation efficacy has a significant positive effect (supporting H4a), and perceived costs has a small negative effect; it is only significant at the 10%-level in both the EUT and RDU model. These results indicate that benefits are more important than cost in explaining the intention to adapt. The variable for time preferences has a positive significant effect in both the EUT and RDU models, which means that people who are willing to give up more today to benefit from that in the future, have a higher intention to adapt (supporting H2).

For the three household budget variables, we only find a significant positive effect for access to credit in the RDU model, and a significant positive effect for yearly savings in the RDU, EUT, and PMT model. The effects that we find for the budget variables are positive, which supports hypothesis H6. The effects are, however, not strong, which suggests that the budget is not an important factor for the intention.

3.1.2 | PMT and TPB

In the PMT model, the expected frequency of drought has a significant negative effect on the intention to adapt, which is the opposite of what we would expect (H3). A limitation of our dataset is, however, that everyone expects a high frequency of drought. Eighty percent of our respondents expected a drought to happen once or twice every year and the lowest expectation is once every six rainy seasons (1.6%) which still means that they expect a drought every 3 years. This means that the entire sample has high risk-perception. This is not surprising because at the moment of the interviews (May 2022) they were experiencing the fourth failed rainy season in a row (WFP, 2023). Because of this, we cannot argue that high risk-perceptions have a negative effect on the intention to adapt. We only find that within a group with high risk-perceptions, people with an even higher expected frequency of drought have a slightly lower intention to adapt. A possible explanation is that a combination of high risk-perceptions and low coping appraisal can lead to fatalism and denial (Bubeck et al., 2018). People might become desperate and do not see adaptation as an option anymore. Adaptation measures like planting drought-resistant crop types or livestock diversification can be effective in moderate droughts, but these types of adaptation measures are not helpful anymore if every rainy season fails.

The main drivers of adaptation behavior in the PMT model are perceived adaptation efficacy and perceived self-efficacy. Both coping appraisal variables have a positive significant effect (supporting H4a and H5a). The three variables in the TPB model are all significantly positive. We find that a higher perceived self-efficacy (or perceived behavioural control), a positive attitude toward adaptation and adaptation by family and friends are all related to a higher intention to adapt (supporting H5a, H5b, and H5c).

3.1.3 | Mixed theory model

In the final model, we combine the variables from the different theories and add additional control variables. The AIC value of goodness of model fit for the mix model is lower than in the first four models, meaning that the variables in the mix model perform better in predicting the intention to adapt. We use the risk attitude parameters of RDU (utility curvature and probability weighting) because the AIC for the RDU model is lower than the AIC for the EUT model.

The only theory variables that stay significant in the mix model are perceived adaptation efficacy, time preferences, probability weighting, perceived self-efficacy, and adaptation by family and friends. This suggests that these five variables are the most important components of the different theories and that costs, household budget, and attitude toward adaptation are less important for the intention to adapt. Another variable that has a significant positive effect is the number of implemented measures. People who have implemented more adaptation measures in the past have a higher intention to also adapt in the future, which is in line with results from previous studies (e.g., Noll et al., 2022; Wens et al., 2021). These results indicate that people who are familiar with adaptation measures, either because they have implemented measures themselves or because they observed them with family and friends, are likely to adapt more in the future.

Finally, we included several control variables to test for the influence of household characteristics. The only variable with a significant effect (at the 10% level) is household size. We find that a larger household size is related to a slightly higher intention to adapt. We also estimated models with age, gender, education level, ethnicity, access to government support and aid, and ward location as control variables, but none of these variables had a significant effect and they did not improve the AIC value of the model.

3.2 | Proportion of intended adaptation measures

In Table 5, we again estimate the EUT, RDU, PMT, TPB, and the mixed model, but now we use an ordinary least squares regression with proportion intended as the dependent variable (Noll et al., 2021). Doing so provides insights into which variables explain why people intend to take more or fewer adaptation measures in general. The coping appraisal variables are now measured as the average perceived costs, perceived adaptation efficacy, and perceived self-efficacy of the household for all remaining adaptation measures. The

bilities part of our experiment. These interaction effects were however not significant and did not improve the AIC scores.

TABLE 5 Ordinary least squares regression, dependent variable: Proportion intended.

	EUT	RDU	PMT	TPB	Mix
(Intercept)	−0.16	−0.21**	0.16	−0.00	−0.44***
	(0.10)	(0.10)	(0.10)	(0.08)	(0.13)
Risk aversion (β EUT)	0.04***				
	(0.01)				
Expected frequency	0.00	0.00	−0.01		0.00
	(0.01)	(0.01)	(0.01)		(0.01)
Relative drought impact	0.00	0.00	−0.00		0.01
	(0.01)	(0.01)	(0.01)		(0.01)
Perceived adaptation efficacy	0.01	0.01	0.01		0.01
	(0.01)	(0.01)	(0.01)		(0.01)
Perceived costs	0.02**	0.02*	0.02		0.03**
	(0.01)	(0.01)	(0.01)		(0.01)
Time preferences	0.02***	0.02***			0.02***
	(0.00)	(0.00)			(0.00)
Yearly expenditure (in 100,000 KSh)	0.02	0.02**	0.01		−0.00
	(0.01)	(0.01)	(0.01)		(0.01)
Yearly savings (in 100,000 KSh)	0.09	0.09	0.16**		0.04
	(0.07)	(0.07)	(0.07)		(0.07)
Access to credit	0.01	0.01	−0.00		0.00
	(0.01)	(0.01)	(0.01)		(0.01)
Utility curvature (β RDU)		0.00			0.01
		(0.03)			(0.03)
Probability weighting (γ RDU)		0.02***			0.02***
		(0.00)			(0.00)
Perceived self-efficacy			−0.00	0.01	0.01
			(0.01)	(0.01)	(0.01)
Attitude				0.03**	0.00
				(0.01)	(0.01)
Adaptation by family and friends				0.03***	0.03***
				(0.01)	(0.01)
#Implemented measures					0.02***
					(0.00)
Ward (Burat = 1)					0.07***
					(0.02)
N	500	500	500	500	500
AIC	−289.11	−298.84	−221.69	−231.74	−315.79

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

main difference with the analysis in section 3.1 (Table 4) is that perceived self-efficacy and perceived adaptation efficacy are not significant (Table 5). Perceived costs now has a significant positive effect in four of the five models (Table 5), which is the opposite of what we would expect according to PMT. Comparing those two tables suggests that the method with adaptation measure specific values (Table 4) is a better method to analyze the influence of the PMT variable on the intention to adapt because it captures the differences in coping appraisal variables within one household for different adaptation measures. The method with aggregate scores for intention to adapt and the coping appraisal variables (Table 5), only captures the difference between households in the overall perceived costs, adaptation efficacy, and self-efficacy of adaptation.

3.3 | Past adaptation

Table 6 shows the results if we take past adaptation as dependent variables instead of the intention to adapt. We use a

TABLE 6 Marginal effects for logistic regression models with clustered standard errors (clustered on household "ID") Dependent variable: Adaptation measure implemented (0 = no,1 = yes).

	EUT	RDU	PMT	TPB	Mix
Risk aversion (β EUT)	0.02***				
	(0.01)				
Perceived adaptation efficacy	0.05***	0.05***	0.03***		0.04***
	(0.01)	(0.01)	(0.01)		(0.01)
Perceived costs	−0.04***	−0.04***	−0.03***		−0.03***
	(0.00)	(0.00)	(0.00)		(0.00)
Time preferences	0.01***	0.01***			0.01***
	(0.00)	(0.00)			(0.00)
Yearly expenditure (in 100,000 KSh)	0.00	0.01	−0.02*		0.02*
	(0.01)	(0.01)	(0.01)		(0.01)
Yearly savings (in 100,000 KSh)	0.10**	0.10**	0.03		−0.03
	(0.04)	(0.04)	(0.05)		(0.04)
Access to credit	0.01***	0.02***	−0.01		−0.01*
	(0.01)	(0.01)	(0.01)		(0.01)
Utility curvature (β RDU)		0.01			−0.01
		(0.03)			(0.03)
Probability weighting (γ RDU)		−0.02**			−0.00
		(0.01)			(0.01)
Utility curvature × Risk averse ($\beta \geq 0.28$)		−0.09***			−0.04
		(0.03)			(0.02)
Probability weighting × Risk averse ($\beta \geq 0.28$)		0.04***			0.01*
		(0.01)			(0.01)
Perceived self-efficacy			0.06***	0.07***	0.07***
			(0.00)	(0.00)	(0.00)
Attitude				0.07***	0.02
				(0.01)	(0.01)
Adaptation by family and friends				0.01	0.01
				(0.01)	(0.01)
Access government support or aid					0.02**
					(0.01)
Gender (Female = 1)					0.02***
					(0.01)
Ward (Burat = 1)					−0.11***
					(0.02)
N	7,515.00	7,515.00	7,515.00	7,515.00	7,515.00
AIC	6,779.07	6,741.40	6,504.93	6,582.35	6,216.60

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

logistic regression model with clustered standard errors and adaptation measure specific values for the coping appraisal variables. We compare these results with the results of the logistic regression model for intention to adapt in section 3.1 (Table 4).

In Table 6 we find significant negative effects for perceived costs, which is what we would expect according to the theories (H4b), but we did not find this effect for the intention to adapt model (Table 4). This difference might be caused by the intention behavior gap (Kesternich et al., 2022), people might underestimate the costs when they state their intention, but when they actually have to perform the behavior (i.e., implement the adaptation measure), the costs become an important factor and people will not implement the adaptation measure if the costs are too high.

A second difference is the effect of the utility curvature and probability weighting variables in the RDU model. We include the interaction effect of the dummy for highly risk averse people ($\beta \geq 0.28$) with both utility curvature and probability weighting, and we find a significant negative effect of utility curvature for this highly risk averse group. This is an unexpected result because it means that people in the highly risk averse group have implemented fewer adaptation measures than people in the group with lower risk aversion. We still find a significant positive effect for the probability weighting coefficient within this group (supporting H1C). A closer examination of the data indicates that this result is probably caused by the fact that risk averse people are only more likely to implement certain types of adaptation measures, not all types of measures (Supporting Information S5 and section 3.4). This is also in line with previous studies that show that risk averse people are more likely to implement low-risk adaptation measures that they are familiar with, but less likely to implement new unknown adaptation measures (Asravor, 2019; Brick & Visser, 2015; Jin et al., 2020; Liu, 2013).

A third difference is that adaptation by family and friends is not significant in Table 6, which indicates that observing adaptation is more important in explaining intention than in explaining past behavior. A likely explanation for this difference is that early adaptors put less value on the social network, while people who put more value on the social network follow later. Finally, we find a significant positive effect for access to government support and aid, which indicates that support by government and aid organizations can stimulate adaptation.

3.4 | Adaptation measures, risk aversion, and livelihood activities

In this section, we analyze differences in adaptation decisions for distinct types of adaptation measures and how this relates to livelihood activities. Especially for risk aversion, we expect to find different effects for distinct types of adaptation measures (H1d) which is why we focus here on EUT and give the results for RDU, PMT, and TPB in Supporting Information S6.

First, we analyzed the relationship between livelihood activities and the implementation of adaptation measures (Supporting Information S5). This resulted in four categories of adaptation measures: livestock-related adaptation, (beekeeping, livestock diversification, insurance, moving further with livestock than normal, pasture conservation, poultry farming, and vaccination of livestock); crop farming adaptation (agroforestry, drought-resistant crops, irrigation, kitchen gardens, and saving groups); entrepreneurial adaptation (staring a small business); and water-related adaptation (digging a borehole or shallow well and rainwater harvesting).

Table 7 and Table 8 give the marginal effects of logistic regression models with as dependent variables the implementation of the fifteen adaptation measures and as independent variables the EUT variables and control variables for household characteristics.[4] We included the interaction effects of *Risk aversion* (β EUT) with both the dummy variables livestock keeper and crop farmer, to analyze if risk averse livestock keepers behave differently than risk averse crop farmers. In the previous sections, we found that risk aversion is associated with more adaptation, but here we find that this does not hold for all types of adaptation measures. For the livestock-related adaptation measures (Table 7), we find a significant and positive effect of the interaction between risk aversion and livestock keeper for three of the seven measures (BK, LD, and PF) and no significant effects for the interaction between risk aversion and crop farmer. For the crop farming adaptation measures (first five models in Table 8), we find a significant positive effect of the interaction between risk aversion and crop farmer for agroforestry (AF) and drought-resistant crops (DC). Whereas, there is a significant negative effect of the interaction between risk aversion and livestock keeper for drought-resistant crops (DC). We thus find that the positive relation between risk aversion and adaptation only holds for some adaptation measures. Risk averse people are more likely to implement adaptation measures that are related to their livelihood activities but less willing to invest in adaptation measures that require a change in their livelihood activities (supporting H1d).

We also find interesting differences between adaptation measures and a few other variables. The effect of the time preference variable is positive for most adaptation measures (supporting H1g), but for drought-resistant crop types (DC) time preferences has a significant negative effect. Planting drought-resistant crops is however mainly relevant for crop farmers, and we therefore include the interaction between crop farmer and time preferences which gives a significant positive effect. For the wealth proxies (access to credit, yearly savings, and yearly expenditure) we find some positive and some negative effects, which suggests that some adaptation measures are more obtainable for low-income households, while other measures can only be implemented by higher-income households. Furthermore, we find that access to government support or aid is positively correlated with the implementation of beekeeping (BK), kitchen gardens (KG), and starting a small business (SB), while it is negatively correlated with moving further than normal with livestock (MO). Finally, we find education and gender effects. Women are more likely to implement kitchen gardens (KG), poultry farming (PF), saving groups (SG), and rainwater harvesting (RH) while men are more likely to implement livestock diversification (LD) and beekeeping (BK). People with higher education levels are more likely to start poultry farming (PF), to participate in savings groups (SG) and to start a small business (SB).

[4] We used the perceived costs and perceived adaptation efficacy of the specific adaptation measure in Tables 6 and 7. The perceived costs and perceived adaptation efficacy variables are therefore different in each model.

TABLE 7 Marginal effects of logit regression for livestock-related adaptation measures with expected utility theory (EUT) variables and interaction effects for risk aversion with livestock keeper and crop farmer.

	Livestock-related adaptation measures						
	BK	LD	IN	MO	PC	PF	VA
Risk aversion × Livestock keeper	0.07***	0.06**	0.01	0.01	−0.02	0.10***	0.01
	(0.02)	(0.03)	(0.00)	(0.01)	(0.02)	(0.03)	(0.01)
Risk aversion × Crop farmer	−0.08	−0.01	0.00	0.03	−0.08	0.13	0.04
	(0.06)	(0.10)	(0.01)	(0.03)	(0.06)	(0.08)	(0.03)
Perceived adaptation efficacy	0.03**	0.10***	−0.00	0.03***	0.04*	0.06**	0.01*
	(0.01)	(0.03)	(0.00)	(0.01)	(0.02)	(0.02)	(0.01)
Perceived costs	−0.03**	−0.04	−0.01**	0.01	−0.03**	−0.06***	−0.02***
	(0.01)	(0.02)	(0.00)	(0.01)	(0.01)	(0.02)	(0.01)
Time preference	0.02***	0.02***	0.00*	0.02***	0.01*	0.03***	0.01***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
Access to credit	−0.02	0.00	−0.00	−0.02	0.04**	−0.07**	0.00
	(0.02)	(0.03)	(0.00)	(0.02)	(0.02)	(0.03)	(0.01)
Yearly savings	−0.05**	−0.13***	−0.01	−0.01	0.02	0.05*	0.02**
(In 100,000 KSh)	(0.02)	(0.04)	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)
Yearly expenditure	0.17	0.38**	0.07*	−0.18*	−0.09	0.01	−0.07
(In 100,000 KSh)	(0.12)	(0.19)	(0.04)	(0.10)	(0.14)	(0.18)	(0.06)
Gender (female = 1)	−0.07**	−0.11***	0.01	−0.01	−0.00	0.20***	−0.01
	(0.03)	(0.04)	(0.01)	(0.02)	(0.03)	(0.04)	(0.01)
Education level	−0.00	0.02	0.00	−0.00	0.01	0.03**	−0.00
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
Access to government support or aid	0.04**	0.04	0.00	−0.04**	0.03	0.04	0.01
	(0.02)	(0.03)	(0.00)	(0.02)	(0.02)	(0.03)	(0.01)
Crop farmer	−0.06	−0.17***	0.00		−0.00	−0.06	−0.05***
	(0.04)	(0.05)	(0.02)		(0.05)	(0.07)	(0.02)
Livestock keeper	0.09***	0.34***	0.03**	0.14***	0.19***	0.04	0.06***
	(0.03)	(0.04)	(0.01)	(0.02)	(0.03)	(0.05)	(0.02)
N	501.00	501.00	501.00	501.00	501.00	501.00	501.00
AIC	371.16	458.20	163.46	349.24	442.54	519.55	257.51

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

4 | DISCUSSION AND CONCLUSION

In this study, we analyzed the drivers and barriers of drought risk adaptation behavior based on four decision-making theories, namely expected utility theory (EUT), rank dependent utility theory (RDU), protection motivation theory (PMT), and theory of planned behavior (TPB). Table 9 summarizes the main results and discusses the advantages and disadvantages of the different theories. A comparison of the performance of the four theories shows that the EUT and RDU models have the best fit to the data in the intention to adapt models (lower Akaike Information Criteria—AIC—scores) while PMT and TPB perform better in the past adaptation models. However, the mixed models perform the best, which indicates that both the economic and the psychological theories also miss important variables. From the economic theories, we observe that the time preference variable and the risk attitude variables (risk aversion in EUT and probability weighting in RDU) remain significant in all regression models. From the psychological theories, we observe that perceived self-efficacy seems to be an important factor that has a positive effect on both the intention to adapt and past adaptation. Moreover, adaptation by family and friends and the number of already implemented adaptation measures have a positive significant effect on the intention to adapt, which suggests that social norms and familiarity with adaptation are important factors in the decision-making process. Studies that utilize economic theory and that want to understand the decision-making process should thus not ignore perceived self-efficacy and underlying attitudes and norms, such as addressed in PMT and TPB.

TABLE 8 Marginal effects of logit regression for crop related adaptation measures, starting a business and water conservation measures, with expected utility theory (EUT) variables and interaction effects for risk aversion with livestock keeper and crop farmer.

	Crop farming adaptation					Entrepreneurs	Water-related adaptation	
	AF	**DC**	**IR**	**KG**	**SG**	**SB**	**BO**	**RH**
Risk aversion × Livestock keeper	0.00	−0.02***	−0.01	0.03	0.04	−0.04	0.01	0.03
	(0.02)	(0.01)	(0.00)	(0.02)	(0.04)	(0.03)	(0.01)	(0.02)
Risk aversion × Crop farmer	0.06**	0.02**	−0.00	0.05	0.13	0.08	0.01	−0.01
	(0.03)	(0.01)	(0.01)	(0.04)	(0.10)	(0.09)	(0.01)	(0.04)
Perceived adaptation efficacy	0.01	0.01*	0.00	0.01	0.04	0.02	0.01	0.09***
	(0.01)	(0.01)	(0.00)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)
Perceived costs	0.01	−0.00	−0.01	0.00	−0.03	−0.05**	0.01	−0.07***
	(0.01)	(0.00)	(0.00)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Time preference	0.00	−0.01***	0.00*	0.01**	−0.01	0.01	0.00	0.01**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Access to credit	0.02	0.01**	0.01**	0.01	−0.02	0.03	−0.00	−0.01
	(0.01)	(0.01)	(0.00)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)
Yearly savings	−0.06	−0.05	−0.01	0.16	1.09***	0.68***	−0.01	−0.04
(In 100,000 KSh)	(0.08)	(0.04)	(0.02)	(0.11)	(0.22)	(0.21)	(0.04)	(0.10)
Yearly expenditure	0.05***	−0.00	0.01*	0.04**	−0.00	−0.01	0.01	0.02*
(In 100,000 KSh)	(0.01)	(0.00)	(0.00)	(0.02)	(0.04)	(0.03)	(0.00)	(0.01)
Gender (female = 1)	0.01	−0.01	−0.01	0.05*	0.21***	0.06	−0.00	0.05**
	(0.02)	(0.01)	(0.01)	(0.03)	(0.05)	(0.05)	(0.01)	(0.02)
Education level	0.00	0.00	−0.00	0.01	0.04**	0.05***	0.00	0.01
	(0.01)	(0.00)	(0.00)	(0.01)	(0.02)	(0.01)	(0.00)	(0.01)
Access to government support or aid	−0.02	−0.00	−0.01	0.04**	0.04	0.09***	0.01	0.02
	(0.01)	(0.00)	(0.00)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)
Crop farmer	0.02	−0.03**	0.09**	−0.03	0.12	−0.19***	0.00	−0.03
	(0.03)	(0.01)	(0.04)	(0.04)	(0.08)	(0.07)	(0.01)	(0.03)
Livestock keeper	−0.04	−0.01	−0.01	−0.15***	−0.04	−0.07	−0.02	−0.02
	(0.03)	(0.01)	(0.01)	(0.05)	(0.06)	(0.06)	(0.02)	(0.03)
Time preference * crop farmer		0.01***						
		(0.00)						
N	501.00	501.00	501.00	501.00	501.00	501.00	501.00	501.00
AIC	266.65	206.55	151.04	395.20	632.79	621.83	135.00	343.65

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

We find mixed results for the effects of perceived costs and perceived adaptation efficacy. Perceived adaptation efficacy has a significant positive effect on the intention to adapt, while the effect of perceived costs is not significant. Perceived costs are, however, a significant factor in past adaptation. A likely explanation for this difference is the intention-behavior gap (Bubeck et al., 2020; Kesternich et al., 2022). Our results suggest that people consider efficacy more than costs when stating their intention, but costs become a barrier to the actual implementation. One reason for studies to use intention as a proxy for adaptation behavior, instead of observed past behavior, is the potential existence of feedback effects between theory constructs and past adaptation. Perceptions can change after implementing a measure, leading to a model that fails to capture the actual causal relationship between constructs and adaptation decisions (Bubeck et al., 2012; Kesternich et al., 2022). Feedback effects are mainly relevant for risk perceptions, as effective adaptation reduces the actual objective risks (Bubeck et al., 2012). Although people might update the perceived costs and perceived adaptation efficacy after implementation, on average we expect no significant feedback effects for perceived costs and perceived adaptation efficacy because actual costs and actual adaptation efficacy do not change after implementation. It is, therefore, likely that the difference in the effect of perceived costs on intention and on past adaptation is caused by the intention behavior gap and not by the feedback effect. Longitudinal data are needed to determine if perceived costs are actually an

TABLE 9 Overview of main results and discussion of advantages and disadvantages of the different theories (partly based on table 2 in Schrieks et al., 2021).

Theory	Main results	Advantages	Disadvantages
Expected utility theory (EUT)	Positive effect of risk aversion, perceived adaptation efficacy and time preferences and negative effect of perceived costs.	Includes risk and time preferences. Full distribution of risk, which can be easily linked to natural disaster risk assessment models. Parameters can be estimated with lab-in-the-field experiments.	Does not include other psychological factors such as perceived self-efficacy, attitudes, and subjective norms insofar as these factors are not captured by the costs and benefits in the utility functions
Rank dependent utility theory (RDU)	Positive effect of probability weighting, perceived adaptation efficacy, and time preferences and negative effect of perceived costs	Same as EUT, but also accounts for non-linearity in probability weighting which leads to a more accurate representation of risk preferences.	Same as EUT
Protection motivation theory (PMT)	Positive effect of perceived adaptation efficacy and perceived self-efficacy. Perceived costs has a significant negative effect on past adaptation, but the effect on intention is not significant.	Combines elements that are part of both economic and psychological theories.	Does not include risk and time preferences.
Theory of planned behavior (TPB)	Positive effect of perceived self-efficacy, attitude, and adaptation by family and friends.	Includes key factors in the cognitive process, such as individual attitudes and subjective norms	Does not include costs and benefits, and risk-and time-preferences. Psychological factors are more difficult to quantify.

important factor in the adaptation decision, but our results indicate that one should be careful with formulating conclusions about adaptation behavior based solely on intentions.

Our results also contribute to the methodological discussion on the measurement of the effects of PMT variables on the intention to adapt. Most existing studies measure one aggregated score per household for the coping appraisal variables and often also for the intention to adapt (Delfiyan et al., 2021; e.g., Gebrehiwot & Van der Veen, 2015; Gebrehiwot & van der Veen, 2021; Keshavarz & Karami, 2016; Van Duinen et al., 2015; Van Valkengoed et al., 2023). This method can only capture the differences between households in general perceptions toward adaptation. Whereas, differences in perceptions for different types of adaptation measures within one household can be important factors in explaining why a household is implementing one adaptation measure and not the other (Jansen et al., 2021; Noll et al., 2022). In our study, we estimated both a regression model with adaptation measure-specific scores for the coping appraisal variables and a regression model with aggregated scores. Perceived self-efficacy and perceived adaptation efficacy are not significant in the models with aggregate scores, but they do have significant positive effects in the models with measure-specific scores. This result confirms the conclusions from Jansen et al. (2021) and Noll et al. (2022) that accounting for adaptation measure-specific effects leads to a more accurate estimation of the intention to adapt. A limitation of our data is that we only have individual scores for each adaptation measure for the coping appraisal variables. Future studies can also measure within household differences for other variables, such as attitudes toward adaptation measures, subjective norms, and the perceived risks of implementing adaptation measures.

Finally, we estimated logistic regression models for each adaptation measure separately. We found a positive effect of risk aversion on adaptation in general, but the analyses of the individual adaptation measures show that this only holds for specific types of adaptation measures. Risk averse livestock farmers are only more likely to implement adaptation measures that are related to pastoralism, and risk averse crop farmers are only more likely to implement adaptation measures that are related to crop farming. We, thus, conclude that risk averse people are more likely to implement adaptation measures that are relatively small adjustments to their current livelihood activities, but they are less willing to invest in adaptation measures that require a switch to alternative livelihood activities. Adaptation measures that require investment in new livelihood activities are likely to be perceived as risky because people are unfamiliar with these alternative livelihood activities. We also observe that the type of adaptation measures that people implement differs with gender, livelihood activity, education level, access to financial resources, and access to government support.

Empirical studies on drought risk adaptation behavior, or adaptation behavior related to other hazards, often make use of one theoretical framework building on insights from one discipline. The advantage of focusing on one theory is that one can go into more detail and expand the knowledge in their field on the relevance of a theory in different contexts. A disadvantage can be that one misses important elements in the adaptation decision that are better modeled in theories from other fields. In this article, we combine insights from economics and psychology by assessing four key theories, which improve our understanding of the key factors that drive adaptation behavior. We do not claim that one theory is better than the other, but by showing the advantages and disadvantages related to the four theories, our approach can help future researchers in deciding which theory to use and potentially help in building new theoretical frameworks that combine elements of the different theories.

A comparison between economic theories and psychological theories is challenging, especially when formalizing the psychological theories. Where the economic theories have developed clear mathematical formalization and well-established experiments to measure for instance risk and time preferences (Charness et al., 2013; Holt & Laury, 2014; Tanaka et al., 2010), quantifying factors such as perceptions, norms, and attitudes is driven by the formalization of these constructs into survey questions. While this has been done, guidelines for measuring these theoretical constructs are not well established in the literature and various studies use different questions, which hampers the comparability of results (Ajzen, 2020; Kothe et al., 2019; Yuriev et al., 2020). We aim to overcome this difficulty, as well as possible, by constructing our survey questions based on previous studies that use these theories in the context of drought adaptation behavior (Arunrat et al., 2017; Gebrehiwot & Van der Veen, 2015; Grothmann & Patt, 2005; Keshavarz & Karami, 2016; Truelove et al., 2015; Van Duinen et al., 2015; Wang et al., 2019; Wens et al., 2021; Yazdanpanah et al., 2014). We hope that future studies build on these questions to create standardized questionnaires and allow comparison across different study areas.

Our results have important implications for policies that aim to stimulate adaptation behavior. Perceived adaptation efficacy and self-efficacy for individual adaptation measures are important in explaining adaptation decisions, which indicates that promoting specific measures might be more effective than influencing the general perceptions toward adaptation. Furthermore, we find that adaptation by family and friends and experience with adaptation have a positive effect on adaptation, which suggests that policies should increase the knowledge about adaptation measures and increase familiarity with adaptation decisions. In the promotion of specific measures, it is important to consider people's risk attitudes, livelihood activities, gender, education level, and access to financial resources. It will require less effort to promote adaptation measures that are relatively small adjustments to current livelihood practices. If one wants to promote new technologies or adaptation measures that require a switch to other livelihood activities, then one should give more attention to reducing (perceived) risks and making people familiar with the adaptation measure, for example with appropriate information and carefully targeted trainings.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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