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BEHAVIOURAL CONTRIBUTORS TO AGRICULTURAL TECHNOLOGY ADOPTION

A TOOLKIT FOR RESEARCHERS AND PRACTITIONERS

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Contents

1. Introduction

In low-income countries, agriculture is the main source of livelihood for 59 percent of the population (World Bank 2019). Uncertainty is inherent in agriculture. Farming entails many elements that lie outside of farmers' control such as (increasingly) weather and pest shocks (Chavas and Nauges 2019; Rosenzweig and Udry 2020; Moscona and Sastry 2021), price fluctuations (Bellemare et al. 2013), the quality of agricultural technologies (Bold et al. 2017; Ashour et al. 2019; Hoel et al. 2022), and other factors. Reducing poverty, improving food security, and charting a path for households out of poverty will require improvements in agricultural productivity (Bridle et al. 2019).

In recent years, many agricultural technologies have become available that can improve productivity and reduce some aspects of uncertainty. However, the adoption of these technologies is often staggeringly low (Aker 2011; Bold et al. 2017; Duflo et al. 2008; Kelly et al. 2003). For example, in Uganda, only 10 percent of maize farmers use hybrid maize that is bred specifically to reduce vulnerability to pests and droughts, only 44 percent use glyphosate herbicide to reduce intensive labour, and only 10 percent use inorganic fertilizer to improve harvests (Gilligan et al. 2019). These figures are even more striking given that farmers tend to know that using these technologies can come with substantial benefits, including increased yields and profits (Ashour et al. 2019).

Additionally, despite potential profitability, new technologies come with their own uncertainty – for example, about their compatibility with farming conditions, potential yields and profits, the quality of the technologies, and market access (Chavas and Nauges 2019). These factors generate uncertainty in returns on investment of the technologies and future earnings. In low resource settings, compounded with credit and insurance constraints, uncertainty poses a key behavioral constraint for farmers (Chavas and Nauges 2019). Specifically, attitudes towards and beliefs regarding uncertainty govern decision-making and behaviors. Consequently, understanding the decision-making process of input adoption can provide insight into how to encourage uptake of productivity-enhancing inputs, thereby providing researchers and practitioners with information on the types of constraints faced by the particular farmers they are targeting and how to alleviate those constraints.

All economic decisions involve some degree of uncertainty. People decide to undertake an action (like adopting a new technology) when they expect that the benefit of the particular action will outweigh the cost. In standard economic theories, there is no uncertainty involved – people know exactly what will happen if they take a particular action – they know the benefits and the costs with certainty. However, that is rarely actually the case. In reality, people do not have full information about the benefits or costs of various decisions they may make – there is some degree of uncertainty. In this case, it is *subjective* beliefs about benefits and costs that determine decisions. To decide whether to take a particular action, people need to *form beliefs* about whether the benefits will outweigh the costs.

What determines the decision ultimately made is beliefs regarding the outcome of an action and individual attitudes or preferences around uncertainty. There are two types of uncertainty: risk and ambiguity. Hardaker et al. (1997) distinguishes the subtle difference between risk and ambiguity under the uncertainty umbrella. Risk is where one does not know the future state of the world, but the payoffs and probabilities of possible outcomes are known, whereas ambiguity is where these probabilities are unknown. For example, let's say a farmer is deciding whether or not to purchase a bag of fertilizer, but the fertilizer may or may not help improve yields. The soil conditions may not be appropriate, the money could be wasted if a pest infestation destroys the crop anyway, or the quality of the fertilizer may be poor. The farmer may believe with certainty that the probability of their yield improving due to using the fertilizer is 60 percent and the chances of their yield not improving is 40 percent. Here, the farmer is facing risk when making their decision of whether to purchase the fertilizer. Of course, knowing the probabilities with certainty is practically impossible, but it is the farmers' beliefs about how certain they are that matters, which leads us to the next type of uncertainty.

The second type of uncertainty is when the probability of each outcome is not known; this constitutes ambiguity, or an ambiguous outcome. For example, the farmer may believe that there is some chance that yield could improve and some chance that it would not. However, they do not know what the probabilities of the two outcomes are. So, they face ambiguity in the decision they are trying to make.

People also have attitudes, termed preferences, regarding how they feel about risk and ambiguity that will determine the decisions they make based on their beliefs. Individuals can be risk-averse, risk-neutral, or risk-loving, and they can be ambiguity-averse, ambiguity-neutral, or ambiguity-loving. Another attitude or preference that affects decision-making is how people value the present versus the future, termed time discounting. When people weigh outcomes in the near-term more heavily than in the future, people are termed myopic, or, they have a high discount rate. The classic example is deciding whether to exercise today – we know exercising has future benefits but we may choose not to because the benefits are realized far in the future and we value those benefits (discount them) less.

Ultimately, the adoption of agricultural technologies in the context of many sources of uncertainty hinges on the preferences and beliefs of farmers – key behavioral aspects of decision-making. This document provides an overview of four behavioral factors that affect decision-making: risk-aversion, ambiguity-aversion, beliefs, and time preferences. When we discuss beliefs, we mean specifically beliefs about uncertainty.

Section 2 discusses risk and ambiguity preferences, Section 3 describes beliefs, Section 4 discusses time preferences, and Section 5 concludes. Each topic is broken down into three parts: the definition of each concept, why it is important, and how to measure it.

2. Risk and ambiguity preferences

2.1. What are they?

Risk- and ambiguity-aversion are attitudes (termed "preferences"), meaning that in economics, they are considered part of the utility function. Consequently, preferences influence people's utility and thus behaviors. Recall that an individual only undertakes an action if the utility (benefit minus the cost) is positive.

Let's start by defining a few terms. A "fair bet" is a wager where the expected value is zero. Let's say that a person is asked to choose whether to take the following bet or to walk away. The bet is that you receive $1 if a flipped coin comes up heads and you pay $1 if a flipped coin comes up tails. There is a 50 percent chance you win $1 and a 50 percent chance you lose $1 – so, if you were to conduct this bet many times, on average, the amount gained would be zero.[1] Someone who is unwilling to make a fair bet is "risk-averse." Someone who is indifferent about a fair bet is "risk neutral." Someone who is "risk loving" will make a fair bet.

Now consider the choice between (i) a bet of known probabilities in which there is a 50 percent chance you win $1 and a 50 percent chance you lose $1 and (ii) a bet of unknown probabilities of winning $1.50 and losing $0.50. An ambiguity-averse person will prefer the first bet of known probabilities despite a higher potential payoff in the second bet. An ambiguity-neutral person will be indifferent between the two bets, while an ambiguity-loving individual will take the bet of unknown risks.

With respect to farming, under risk, a farmer may not know whether there will be a drought or not, but they may believe that, based on their prior experience, the likelihood of a drought in any particular year is 50 percent. Under ambiguity, the farmer does not know whether a drought will occur this year but also does not know the probability of a drought occurring. Individuals exhibit different degrees of aversion to both risk and ambiguity.

Another concept is prospect theory, which argues that individuals place more weight on losses than gains, thus being risk-averse in the loss domain and risk-loving in the gain domain (Kahneman and Tversky 1979; Tversky and Kahneman 1992). Under loss aversion, even with the safe bet of winning $1 with 50 percent probability or losing $1 with 50 percent probability, an individual will gain more utility from winning $1 than the utility they would lose from losing $1. Loss aversion also factors into individual decision-making.

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[1] The calculation is (1 * 0.5) + (-1 * 0.5) = 0.

2.1. Why are risk and ambiguity important?

Technology adoption decisions are determined by risk- and ambiguity-aversion – those who are risk-/ambiguity-averse are less likely to adopt new technologies and can be more hesitant even when they have some experience with the technology. For those who are risk/ambiguity neutral, their preferences are such that the risk and ambiguity parameters do not affect utility. Those who are risk/ambiguity loving are more likely to adopt a new technology since they are willing to take bets for a potential reward even if the probability of winning the bet is less than 50 percent.[2]

There is a large body of research on the relationship between risk preferences and farming decisions (Binswanger et al. 1980, Kebede 1992, Goodwin and Kastens 1996, Abadi Ghadim et al. 2005). It is well-documented in the literature that risk-aversion reduces adoption of agricultural technologies (Simtowe 2006; Dercon and Christiaensen 2011) around which there is uncertainty. Liu (2013) supports this hypothesis when explaining why some cotton farmers in China waited ten years before adopting Bt cotton despite its promising pest-resistant features. The findings show that farmers who are more risk-averse and loss-averse are more likely to adopt Bt cotton later than others. In an experimental game in South Africa, even in the presence of insurance, risk-averse subsistence farmers prefer conventional rather than improved seeds and are less likely to use modern farming inputs (Brick and Visser 2015).

More recent empirical evidence suggests that adoption behaviors are more aligned with prospect theory. Using prospect theory, Tanaka et al. (2009) suggest that loss aversion is a key characteristic that Vietnamese farmers exhibit, and they advocate for moving beyond the expected utility framework to understand behaviors under uncertainty. Bocquého et al. (2014) report that French farmers are twice as responsive to losses as to gains and tend to overweight small probabilities of extreme outcomes, further reducing the likelihood of taking up a new technology.

A growing number of studies have examined risk and ambiguity preferences side by side and many suggest that ambiguity seems to be a more influential factor in low rates of adoption. Engle-Warnick et al. (2011) find that risk-averse Peruvian farmers are more likely to plant more than one main crop while ambiguity-averse farmers are less likely to diversify types of crops as well as varieties within a main crop. Limited varietal diversification among ambiguity-averse farmers stems from their limited information about new crop varieties. The main crops, potato and maize, are considered as relatively safe in terms of yields and market demand. But new crop varieties have different properties that lead to ambiguity in returns. This suggests ambiguity in the information about yield or price distributions of new varieties.

Crentsil et al. (2020) examine the relationship between risk/ambiguity preferences and adoption rates across time. They find that risk-averse aquafarmers

[2] See Elabed and Carter 2015, Ward and Singh 2015, Barham et al. 2014, Ross et al. 2012, Engle-Warnick et al. 2008, and Engle-Warnick et al. 2007.

in Ghana adopt three new technologies designed to reduce risk: a new tilapia breed that is more disease-resistant, extruded feed to reduce the risk of water contamination, and floating cages to reduce the risk of natural predators. Thus, risk-averse farmers exhibit a high adoption rate. In contrast, ambiguity-aversion slows down the uptake of floating cages, which involves large fixed costs, while having no effect on the other two technologies. The large initial investment of the floating cages prevents farmers from conducting small experiments to help with learning and reduce ambiguity. Conversely, Bryan (2019) argues that the rate of adoption of new crops under partial insurance among ambiguity-averse farmers is lower compared to their ambiguity neutral counterparts. The value of partial insurance is contingent on the probability of a specific state of the world as well as earnings in that state. Thus, when yields of new crops are uncertain or ambiguous, this insurance product would be less attractive to ambiguity-averse farmers.

In contrast to the more common pattern that ambiguity-aversion behaviors are associated with lower adoption rates, Barham et al. (2014) find that ambiguity-averse farmers in the United States *speed up* the adoption of genetically modified (GM) corn. The authors argue that the insect-resistance technology in GM corn reduces ambiguity with respect to pest damages, and thus alleviates the constraint on ambiguity-averse farmers. However, in the U.S., farmers are generally more educated and have greater access to information and agricultural extension services on new seed varieties from which they can acquire information that reduces their uncertainty.

2.2. How do you measure risk- and ambiguity-aversion?

To measure preferences, lab-in-the-field experiments are commonly used. Lab-in-the-field experiments are hypothetical choices that respondents are asked to make. Usually, they involve presenting a respondent with a set of lotteries or choices, asking the respondent to choose their preferred one, and then making a payment to the respondent that reflects their choice.[3] The foundation of many experiments stems from a methodology developed in Holt and Laury (2002), which is a multiple price list design, presented in Table 1. Respondents face a menu of lottery pairs between a safe bet (Option A) and a risky bet (Option B) with same probabilities in each pair but different payoffs (note the expected payoff difference is not shown to respondents). They are asked to choose between Option A or Option B sequentially through the list. The design is embedded with a switching point where the expected payoffs from Option B exceed Option A. The design allows for measurement of the degree of risk aversion and estimation of its functional form. A risk-neutral person would choose

[3] Not all experiments must entail an actual payment. It is generally preferred, as a respondent then has more of an incentive to answer truthfully, but it is not always necessary if it is not logistically or financially feasible. When using non-incentivized methods, it is important to be clear about the method that was used.

Option A in the first 4 items and then switch to Option B. A higher number of A choices indicates a higher level of risk-aversion. The risk-aversion classifications are specified in Table 2.

Table 1: The Multiple Price List for Eliciting Risk Preferences

Option A	Option B	Expected payoff difference
1/10 of \$2.00, 9/10 of \$1.60	1/10 of \$3.85, 9/10 of \$0.10	\$1.17
2/10 of \$2.00, 8/10 of \$1.60	2/10 of \$3.85, 8/10 of \$0.10	\$0.83
3/10 of \$2.00, 7/10 of \$1.60	3/10 of \$3.85, 7/10 of \$0.10	\$0.50
4/10 of \$2.00, 6/10 of \$1.60	4/10 of \$3.85, 6/10 of \$0.10	\$0.16
5/10 of \$2.00, 5/10 of \$1.60	5/10 of \$3.85, 5/10 of \$0.10	−\$0.18
6/10 of \$2.00, 4/10 of \$1.60	6/10 of \$3.85, 4/10 of \$0.10	−\$0.51
7/10 of \$2.00, 3/10 of \$1.60	7/10 of \$3.85, 3/10 of \$0.10	−\$0.85
8/10 of \$2.00, 2/10 of \$1.60	8/10 of \$3.85, 2/10 of \$0.10	−\$1.18
9/10 of \$2.00, 1/10 of \$1.60	9/10 of \$3.85, 1/10 of \$0.10	−\$1.52
10/10 of \$2.00, 0/10 of \$1.60	10/10 of \$3.85, 0/10 of \$0.10	−\$1.85

Source: Holt and Laury (2002).

Table 2: Risk-Aversion Classifications Based on Lottery Choices

Number of safe choices	Range of relative risk aversion for $U(x) = x^{1-r}/(1-r)$	Risk preference classification
0–1	$r < -0.95$	highly risk loving
2	$-0.95 < r < -0.49$	very risk loving
3	$-0.49 < r < -0.15$	risk loving
4	$-0.15 < r < 0.15$	risk neutral
5	$0.15 < r < 0.41$	slightly risk averse
6	$0.41 < r < 0.68$	risk averse
7	$0.68 < r < 0.97$	very risk averse
8	$0.97 < r < 1.37$	highly risk averse
9–10	$1.37 < r$	absolute risk averse

Source: Holt and Laury (2002). *U(x)* is the utility function of payoff *x* and *r* is the risk preference parameter.

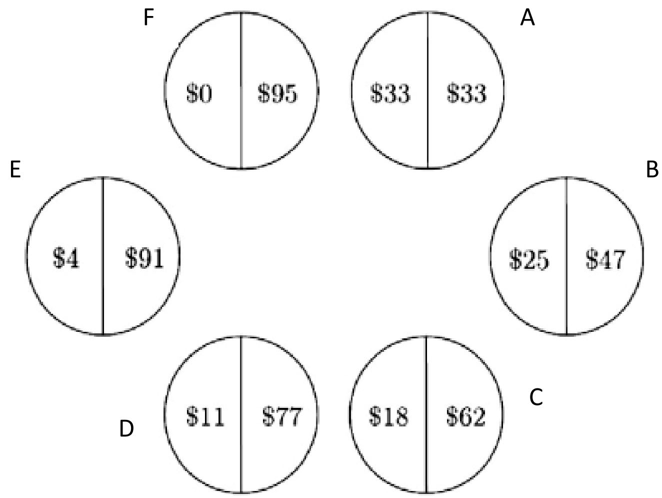
The concept of ambiguity in separation from risk is first mentioned in the thought experiments in Ellsberg (1961). Later studies have adapted the two-color urn game used in the Ellsberg (1961) experiment to measure ambiguity-aversion. In the original Ellsberg (1961) experiment, respondents are presented with two urns of 100 balls. The first urn (Urn I) contains a mix of red and black balls, but respondents do not know how many of each. Meanwhile, the second urn (Urn II) contains exactly 50 red and 50 black balls. The respondents are then asked to make four choices:

1. Drawing from Urn I, choose between winning $100 if a red ball is drawn or winning $100 if a black ball is drawn. Or are you indifferent?
2. Drawing one ball from Urn II, would you prefer that you win $100 if a red ball is drawn or $100 if a black ball is drawn?
3. You can win $100 if you draw a red ball. Would you prefer to draw from Urn I or Urn II?
4. You can win $100 if you draw a black ball. Would you prefer to draw from Urn I or Urn II?

Ellsberg (1961) does not propose how to measure ambiguity-aversion per se and mainly focuses on pointing out the violation of rationality, suggesting that another aspect other than risks is at play. Crentsil et al. (2020) adapt this game by asking the respondents how much he/she would be willing to pay to play the lottery using Urn I and Urn II. The difference in willingness to pay between these two urns is a continuous measure for aversion to ambiguity, in which the larger the difference, the higher the level of ambiguity-aversion.

Risk and ambiguity preferences can be elicited arguably more simply through an approach Cardenas and Carpenter (2013) introduce. The questions are presented in binary lotteries in multiple rings, see Figure 1. Note that all the rings are divided into two halves, symbolizing that the probabilities of each payoff are the same – 50 percent. The expected value increases with the variance of the payoff (the difference between the high value and the low value). Participants are asked to choose one of the six 50-50 lotteries (labeled A – F) they would like to play in which the odds of a high payment are the same as the odds of a low payment. As one moves clockwise around the figure, the lotteries increase in risk and expected payoff except for the last lottery, which has the same expected payoff as the fifth but is riskier. The participant's risk preferences are revealed by the chosen lottery. To determine payouts for the task, the experimenter uses a bag of five low value balls and five high value balls where the ball values are determined by the chosen lottery and the participant blindly picks a ball from the bag.

Figure 1: Lottery choices to assess risk preferences

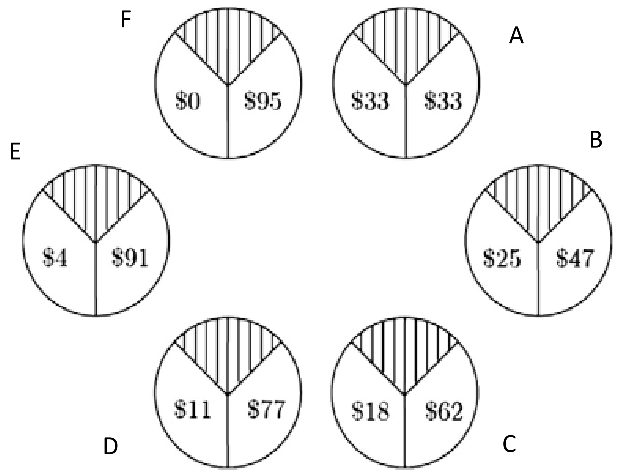


Source: Cardenas and Carpenter (2013).

Assuming the constant relative risk-aversion (CRRA) utility function, each choice is associated with an interval of coefficients of relative risk aversion *r*. Specifically, picking A indicates extreme risk-aversion, $r > 1.77$. Picking B indicates $0.82 \leq r \leq 1.77$ or risk-aversion, C indicates $0.48 \leq r \leq 0.82$ or moderate risk-aversion, D indicates $0.28 \leq r \leq 0.48$ or moderate risk-seeking, E indicates $0 \leq r \leq 0.28$ or risk-seeking, and picking F indicates $r \leq 0$ or extreme risk-seeking (Cardenas and Carpenter, 2013).

To measure ambiguity-aversion, a similar method can be used. Instead of dividing the circles into halves, the circles can include a shaded region to represent unknown probabilities. In Figure 2 below, the chance of a high payout is at least 30 percent, as is the chance of a low payout. The shaded part covers the rest of the circle (40 percent), which can be interpreted as the probability of the high payout being between 30 and 70 percent, and the probability of the low payout being between 30 and 70 percent. The individual does not know what the probabilities of the two payouts is, but only knows the range. Participants are asked to choose one of six lotteries (again labeled A – F) in which the odds of a high or low payment are bound between 3/10 and 7/10 but are unknown. To determine payouts for the task, the experimenter uses a bag of ten balls. The participant knows that there are at least three low value balls and three high value balls in the bag but does not know the distribution of the remaining four balls which could be either low or high value. The participant blindly picks a ball from the bag and then receives the payout listed in the lottery they chose.

Figure 2: Lottery choices to assess ambiguity preferences



Source: Cardenas and Carpenter (2013).

To determine whether an individual is ambiguity-averse, neutral, or loving, one needs to use the selection from both sets of lotteries in Figures 1 and 2. Similar to risk preferences, each choice is also associated with an interval of coefficients of relative risk aversion *r*, as shown above. The degree of ambiguity-aversion is the difference in the coefficients of relative risk aversion *r* between the choice selected in Figure 2 and Figure 1. If the difference is positive, meaning that a person selects a higher numbered lottery in the second choice than the first choice, he/she is considered ambiguity-averse. If the difference is zero, meaning that the person selects the same number in both lotteries, then he/she is ambiguity-neutral. If the difference is negative, meaning that a person selects a lower numbered lottery in the second choice than the first choice, he/she is considered ambiguity-loving.

A more simple and straightforward approach is to administer risk and ambiguity questions in a qualitative way. These tend to be very simple questions that ask a respondent to agree or disagree on a 5-point Likert scale. While the questions are easier for respondents to understand and respond to, the granularity and precision of the information is reduced. With the quantitative approaches proposed above, risk and ambiguity parameters of the utility function can be determined, which is not the case with the qualitative questions, which are simply used to classify people into more general groups. Gilligan and Karachiwalla (2020) shows that qualitative questions better aligned with predicted patterns compared to quantitative questions in a survey administered using both methods in Uganda.

Table 3: Qualitative survey questions to measure risk and ambiguity

Risk –aversion (qualitative)
I am going to read you a series of statements. Please tell me whether you agree or disagree, and to what degree you agree or disagree. You can also choose to neither agree nor disagree.

Enumerator: read all options to the respondent for each question and read the options using the same tone each time.

	Question	Response codes	Response
Q02	Relative to other people in my community, I am willing to take risks in my life. Do you:	1- Strongly agree 2- Agree 3- Neither agree nor disagree 4- Disagree 5- Strongly Disagree	
Q03	Relative to other people in my community, I am willing to take risks in agriculture (for example, trying new products or brands). Do you:	1- Strongly agree 2- Agree 3- Neither agree nor disagree 4- Disagree 5- Strongly Disagree	
Q04	Let's say next season you go to your local shop to purchase maize seed, and they only have two choices of seed for the same price: • Seed A has very high yields when the rains are enough, but has very low yields when the rains are little. • Seed B has medium yields regardless of whether the rains are enough or little. If you know that there is equal chance of enough rain and of little rains next season. Which seed would you buy?	1- Seed A 2- Seed B	

Ambiguity aversion (qualitative)
I am going to read you another series of statements. Please tell me whether you agree or disagree, and to what degree you agree or disagree. You can also choose to neither agree nor disagree.

Enumerator: read all options to the respondent for each question and read the options using the same tone each time.

	Question	Response codes (read)	Response
Q05	It disturbs me when I am uncertain of the effects of my actions. Do you:	1- Strongly agree 2- Agree 3- Neither agree nor disagree 4- Disagree 5- Strongly Disagree	
Q06	I am comfortable in situations in which I do not know the likelihood of different outcomes. Do you:	1- Strongly agree 2- Agree 3- Neither agree nor disagree 4- Disagree 5- Strongly Disagree	
Q08	If the benefits of a product (such as herbicide or fertilizer) are not well known, then compared to other people in my community I will tend to invest less in it. Do you:	1- Strongly agree 2- Agree 3- Neither agree nor disagree 4- Disagree 5- Strongly Disagree	
Q09	When deciding which agricultural inputs to purchase, I tend to purchase products that I have tried before. Do you:	1- Strongly agree 2- Agree 3- Neither agree nor disagree 4- Disagree 5- Strongly Disagree	
Q10	In a season when people do not know how good the rains will be, I tend to grow a smaller garden of maize. Do you:	1- Strongly agree 2- Agree 3- Neither agree nor disagree 4- Disagree 5- Strongly Disagree	

Source: Gilligan et al. (2019).

3. Beliefs about uncertainty

3.1. What are they?

Theoretical economic models mentioned above assume that objective probabilities are known to decision makers and that decision makers are rational, however, this is rarely the case in reality. Under the **subjective** expected utility framework, Savage (1954) states that in a risky setting, an agent's optimal decision is determined by (i) their attitude toward risk, and (ii) their subjective belief regarding the probability of an uncertain outcome occurring (economists now add in attitudes towards ambiguity as well). In the agricultural technology adoption setting, embedded in their decision-making process, farmers form their own subjective probabilities through some initial beliefs about the returns to a new technology. As part of their learning, farmers update their beliefs through additional information they receive from extension agents or learn from their own experiences and farming networks (Lybbert et al. 2007).

3.2. Why are they important?

Given that there are many uncertainties and moving factors in farming decisions related to new technologies, forming and updating beliefs is the foundation for farmers' many adoption choices. For example, in Laos, farmers' beliefs about the prevalence and effects of insects on production affect the frequency with which farmers spray rice fields with insecticides (Heong et al., 2002). Shikuku et al. (2019) explore multidimensional beliefs of orange-fleshed sweet potato (OFSP). Specifically, they examine farmers' perceptions of nine dimensions of OFSP, including its health benefits, taste, yield, storability, sweetness, children enjoying eating, disease tolerance, maturity length, and color. They find that these beliefs are positively associated with the likelihood of adopting the OFSP variety and increasing the proportion of its production.

One specific constraint to adoption that has more recently been identified is the prevalence and perceived prevalence of low-quality agricultural inputs such as fertilizer, hybrid maize seed, and glyphosate herbicide. Bold et al. (2017) document that low-quality fertilizer and hybrid maize seeds in the Ugandan market they study are widespread. Specifically, retail fertilizer has 31 percent less nitrogen than the label claims, and hybrid maize only has 50 percent authentic seeds. Meanwhile, when asked about their beliefs of the nitrogen content in fertilizer, farmers as a group do report a level of expected nitrogen similar to the tested samples. This suggests that they learn about the low-quality inputs and associate them with lower yields to a certain extent.

Complementary to the findings in Bold et al. (2017), Ashour et al. (2019) show that it is also common to find sub-par quality herbicide with an average of 15 percent of glyphosate missing herbicide bottles in parts of Uganda. Farmers in their sample believe in the benefits of authentic herbicide but are aware of the low-quality issue in their local market. However, compared with the measured quality of herbicide at local markets, farmers' beliefs of the quality are not very accurate. Additionally, the variation in herbicide quality and market prices are correlated but at a very small magnitude, suggesting that farmers do not have full information about the product quality for the prices to adjust. The findings from these two studies provide a possible explanation for farmers' low adoption rates of these inputs.

Farmers can update their beliefs as they gather more information about the innovations through various information services (see Bridle et al. 2020 for a review). Through an experiment that provided farmers with information about a new hybrid maize variety along with sample seed packs, Tjernstrom and Gars (2019) uncover the process of updating beliefs among Kenyan farmers. First, farmers in treated villages exhibit higher expected yields of their preferred hybrid maize variety by 7 to 9 percent and are 20 percentage points more likely to prefer the newly introduced seeds over other options. However, farmers put more weight on bad experiences by other farmers in the village when updating their beliefs, leading to a decrease in expected yields. Further, they find that the expected mean yield of farmer's preferred hybrid increases the probability of cultivating hybrid maize in general and the new hybrid variety in particular, providing evidence that farmers change their behaviors based on beliefs that were updated through the intervention.

Hoel et al. (2022) point out that in comparison with other studies, the measured low-quality fertilizer in Bold et al. (2017) is an outlier in the literature. Despite reliably good quality fertilizer in the region, not only do Ugandan and Tanzanian farmers persist their incorrect beliefs about sub-par quality, they are also uncertain about their own beliefs. In explaining this puzzling phenomenon, the authors argue that what is observable to farmers is how the fertilizer looks (for example, whether it is discolored or clumpy). However, despite these visible traits not affecting the efficacy of the fertilizer, farmers may misattribute low yield outcomes to perceived bad quality fertilizer. When they are ambiguous about the likelihood of good quality input, farmers develop multiple priors as possible beliefs, such as "it could be that 50% of fertilizer is fake, but it could be as bad as 90 or 100% fake." The combination of misattribution and multiple priors leads to farmers' sustaining their incorrect beliefs while remaining uncertain.

In another study, Tjernstrom et al. (2021) study the impact of customized information in a virtual interactive farming app on maize farmers' beliefs in Kenya. The experiment allows farmers to experiment with the use of fertilizer and lime on virtual maize plots that are similar to their own. The virtual app provides an interactive platform for farmers to learn and experiment with the properties and performance of a new technology. After interacting with the app, farmers exhibit higher expected maize yields upon using fertilizer and fertilizer plus lime. In the game, farmers with more acidic soil respond to the use of lime on their plots while those with a suitable range of soil pH levels for maize use less. The findings suggest that farmers learn and respond to the use of technology according to their own farming conditions, at least in the game.

Another channel for updating beliefs is through social learning, in which farmers learn from others' experiences (Munshi 2004, Bandiera and Rasul 2006, Conley and Udry 2010). Maertens (2017) studies the adoption of Bt cotton in India that involves less use of pesticides while increasing yields and disentangles the difference between social learning and social pressures. There is a positive relationship between farmers' expected yield of Bt cotton and their likelihood of cultivating Bt cotton. In addition, the author finds evidence that farmers strategically delay adoption behavior until more progressive farmers, or the so-called early adopters, experiment and take up the technology. This emphasizes that farmers learn from a group of progressive farmers but not from ordinary network neighbors. On the other hand, given that Bt cotton has negative externalities on the environment and livestock, the presence of social pressure inhibits farmers' adoption rate. Other work has also found that farmers place a higher weight on information that comes from people in senior or leadership positions (Bridle et al. 2020).

3.3. How do you measure people's beliefs?

Delavande et al. (2011) provide a comprehensive review of the methods used to elicit subjective expectations (beliefs). Three main methods of eliciting beliefs include (i) non-probabilistic methods, or so-called non-cardinal measures, (ii) probabilistic methods without visual aids, and (iii) probabilistic methods with visual aids. Manski (2004) argues in favor of probabilistic methods over non-probabilistic methods. One of the main reasons is that the probabilistic measures allow researchers to calculate more information such as moments of distributions, subjective probabilities of events, and expected utilities.

One way to implement the non-probabilistic method in a survey is by asking questions with Likert scales. For example, the researcher can administer questions such as "How likely it is that your profits next month will be under $300?" with the answers on a Likert scale of "very likely, likely, unlikely, or very unlikely." The disadvantage of using a Likert scale is that respondents can interpret each answer choice on the Likert scale differently, posing a challenge in standardizing and interpreting the results (Delavande et al. 2011). Very likely can mean 95 percent to one person and 80 percent to another.

Another way to use the non-probabilistic method is to directly ask the respondents about their expectations. For example, Jensen (2010) and Nguyen (2008) ask their respondents, "How much do you think you will earn" under different scenarios. While this way is simple and direct, it faces the criticism that it is unclear what statistics the respondent has in mind when answering this kind of question, whether it is the mean, median, mode, etc.

To use probabilistic methods without visual aids, researchers can directly ask the respondents about their subjective probabilities. This method has been implemented in both developed and developing countries. Delavande et al. (2011) give an example of a study by Dominitz and Manski (1997), in which they ask the respondents the percent chance they will be employed by a specific date. Another example is in Attanasio and Kaufmann (2009), in which they elicit expected income among junior high school students in Mexico. They first ask the maximum and minimum level they could earn. Then, they calculate the midpoint M and ask, "From 0 to 100, what is the probability that your earnings at that age will be at least M?" While this method allows researchers to get at percentiles of a subjective probability distribution, calculating other statistics and moments of distributions from these percentiles requires additional assumptions.

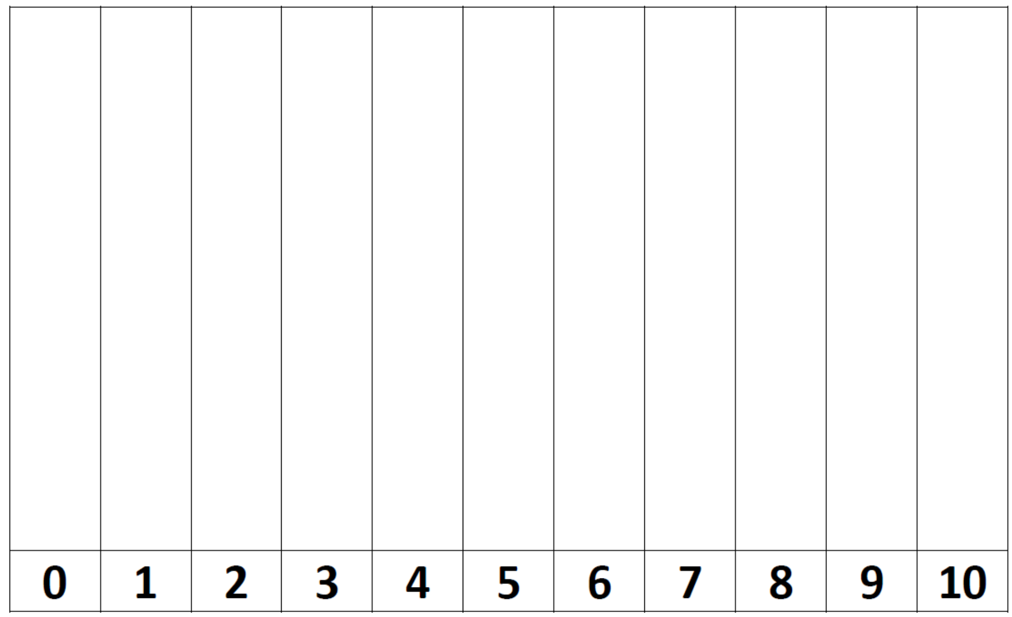
In some contexts where the respondents have less formal education and/or less understanding of percentages or probabilities, eliciting subjective probabilities through visual aids can help respondents conceptualize probabilities. The process entails asking respondents to allocate stones or beans into a number of bins. Lybbert et al. (2007) study the subjective probabilities of rainfall in certain states among Ethiopian and Kenyan pastoralists. They conducted the elicitation process by asking the respondents to distribute 12 stones across 3 piles representing above normal, normal and below normal levels of rainfall. Delavande et al. (2011) argue that such studies still face the issue of varying interpretation similar to the use of Likert scales ("normal" is subjective). While whether explicitly linking the allocation to a probability would help minimize this issue remains an empirical question, Delavande and Kohler (2009) do so in Malawi by reading the following instruction to the respondents:

> *"I will ask you several questions about the chance or likelihood that certain events are going to happen. There are 10 beans in this cup. I would like you to choose some beans out of these 10 beans and put them in the plate to express what you think the likelihood or chance is of a specific event happening. One bean represents one chance out of 10. If you do not put any beans in the plate, it means you are sure that the event will NOT happen. As you add beans, it means that you think the likelihood that the event happens increases. For example, if you put one or two beans, it means you think the event is not likely to happen but it is still possible. If you pick 5 beans, it means that it is just as likely it happens as it does not happen (fifty–fifty). If you pick 6 beans, it means the event is slightly more likely to happen than not to happen. If you put 10 beans in the plate, it means you are sure the event will happen. There is not a right or wrong answer, I just want to know what you think. Let me give you an example. Imagine that we are playing Bawo* [a game]. *Say, when asked about the chance that you will win, you put 7 beans in the plate. This means that you believe you would win 7 out of 10 games on average if we play for a long time."*

Using this information, they can see which outcome people think is most likely on average, and how intensely people feel about a particular outcome. They can also conduct analysis such as what characteristics may predict people's beliefs – for example, more women may believe that a specific event may occur compared to men, or how people's beliefs are associated with their adoption behaviors.

The level of detail in beliefs can be varied. In Gilligan and Karachiwalla (2020), they ask farmers to report how many bottles of herbicide would be fake if they went and purchased 10 bottles at their local market. They provide respondents with 12 buttons and the visual aid presented in Figure 3, which shows slots for 0 – 10 bottles being fake. They ask them to place buttons in the slots based on how likely they think it is that that number of bottles is fake. With this information, they can additionally examine the spread, or variance, of beliefs. If the respondent's buttons are very spread out (for example, there are beans in bins 3-7), it means that they are very uncertain about the likelihood of the different outcomes – they face a lot of ambiguity. If the respondent's buttons are clustered close together (say all in bins 3 and 4) then they face much less ambiguity. As we learned above, this information, coupled with measured risk and ambiguity preferences, can strongly predict adoption behavior.

Figure 3. Beliefs elicitation visual aid



4. Time preferences

4.1. What are they?

Time preferences represent the extent to which an individual values some benefit or payout today over some future time horizons. Individuals generally discount the future. The more impatient an individual is, the more he/she prefers a benefit or payout today compared to the future. The classic example is the decision to exercise – we all know the benefits of exercising, but we often choose not to because we will bear the cost now and will only realize the benefits much later. The "discount rate", how much an individual discounts the future, is also captured as part of the utility function. People who are considered "impatient", "present-biased", or "myopic", have a high discount rate, meaning that they discount the future.

4.2. Why are they important?

As the technology adoption process entails choices made in the present to bring about returns in the future, farmer attitudes toward events along the time horizon matter for their decisions today. Thus, farmers' time preferences have long been considered as integral to explaining adoption behaviors. In examining the origin of variations in time preferences across countries and regions, Galor and Ozak (2016) find that the agro-climatic characteristics during the pre-industrial era that induced higher returns to agricultural investment in some countries have a positive and persistent effect on people's patience even now. Here the long-term orientation is defined as "the cultural value that stands for the fostering of virtues oriented toward future rewards, perseverance, and thrift." In societies where there were higher returns, people were more patient – they were willing to wait for future benefits. In addition, this effect persists for second-generation migrants whose parents come from countries with higher returns.

These results suggest that those who share similar agro-climatic zones would display similar time preferences. Indeed, Ambali et al. (2022) also support this hypothesis. Despite taking place in a different context, the study finds evidence of spatial dependence in time preferences of rice farmers in Nigeria, meaning that rice farmers in the same areas exhibit similar behaviors, and most are impatient. When examining the correlation between socio-economic characteristics and intertemporal decisions, the authors show that age, religion, marriage, locations, and spatial dependence significantly explains rice farmers' level of impatience.

Various studies show that present bias has a negative association with farmers' technology adoption choices. Impatient farmers prefer innovations that generate immediate results in a short term. In Le Cotty et al. (2018), maize producers in Burkina Faso with one standard deviation lower in discounting behavior use 6.5 percent more in the total amount of fertilizer. Similarly, grape farmers in China are also impatient and place less weight on future benefits of rain covers, the technology that protects grapes from future weather variabilities. In addition, Duflo et al. (2011) show that farmers in Western Kenya underestimate their impatience for the future and procrastinate in purchasing fertilizer until the last minute. They find that one solution is to offer free delivery of fertilizer, which increases the adoption of fertilizer by 47 to 70 percent.

Time preferences also affect credit decisions that will eventually affect technology adoption choices. Credit can often help farmers invest in new technologies since they may not always have the requisite liquid cash to make those investments so they can borrow instead. In examining the effects of providing access to credit on agricultural technology adoption, Chowdhury et al. (2020) explore the heterogeneous impacts for different discount rates. When randomly offering farmers with a standard microcredit contract the choice of a weekly repayment, one with a three-month grace period, and a choice between the two types, they document that farmers with present bias behaviors select out of the grace period while those with time consistent preferences tend to prefer the contract flexibility. They conclude that an increase in credit access induces the take-up of new agricultural technologies for present-biased farmers.

4.3. How do you measure time preferences?

Similar to risk and ambiguity preferences, there are two main methods of eliciting time preferences in the literature, one through lab-in-the-field experiments and another through field surveys. While a lab-in-the-field experiment provides the advantage of simplifying the abstract concept through hypothetical scenarios, a field survey generally assesses the discounting behaviors through real-life intertemporal decisions. Frederick et al. (2002) argue that experimental elicitation provides a more precise measure of time preferences due to its isolation from complex real-world decisions, allowing researchers to control for other factors that may influence discounting behaviors (for example, the amount of money a person happens to have at that time). In fact, this method is the most commonly used to elicit time preferences across studies reviewed in this paper.

In experimental studies, the elicitation procedure can be done through choice tasks, matching tasks, pricing tasks, or ratings tasks (Frederick et al., 2002). Among these methods, choice tasks are the most commonly used, followed by matching tasks. Choice tasks to elicit discount rates were introduced by Pender (1996) and Coller and Williams (1999), similar to the multiple-choice list design from Holt and Laury (2002). Instead of varying the risk dimension in risk preferences, respondents face a series of choice pairs between a smaller but more immediate payoff and a larger but more delayed payoff. The menu of choices can be used to derive the bounds on the respondent's discount rate (Duquette et al., 2012). An example of the multiple-choice list from Le Cotty et al. (2018) is shown in Tables 4a and 4b. In the first set of choices, respondents are asked to select between receiving a particular amount today, or a higher amount (of varying size) in five days. In the second set of choices, respondents are asked to make the same decisions, but the choice is between a one month or two months, aiming to elicit the one-month delay discount rate. A higher δ indicates more patience.

Table 4a: Measuring time preferences over a short horizon

For each choice 1 – 9 on the list, respondents are asked, "would you prefer to get A in one day or B in five days?"

	A	B	range of δ	
1	10,000	10,400	0	0.016
2	10,000	10,700	0.016	0.027
3	10,000	11,000	0.027	0.039
4	10,000	11,500	0.039	0.057
5	10,000	12,000	0.057	0.076
6	10,000	13,000	0.076	0.111
7	10,000	14,000	0.111	0.144
8	10,000	17,000	0.144	0.236
9	10,000	20,000	0.236	0.320

Note: Column 'range of δ' indicates the associated interval for monthly discount rate δ for a respondent who switches from A to B.

Table 4b: Measuring Time Preferences over a longer time horizon

For each choice 1 – 9 on the list, respondents are asked, "would you prefer to get A in one month or B in two months?"

	A	B	range of δ	
1	10,000	12,000	0	0.06
2	10,000	15,000	0.06	0.13
3	10,000	18,000	0.13	0.19
4	10,000	20,000	0.19	0.23
5	10,000	23,000	0.23	0.28
6	10,000	29,000	0.28	0.38
7	10,000	48,000	0.38	0.60
8	10,000	75,000	0.60	0.83

Note: Column 'range of δ' indicates the associated interval for monthly discount rate δ for a respondent who switches from A to B.

Other variations of choice tasks include a double multiple price list and a convex time budget to take into account of the confounding effect of utility function curvature (Andreoni et al. 2015). When thinking about time preferences, utility is assumed to be linear, reflecting risk neutrality. However, Andersen et al. (2008) points out that if utility is actually concave, reflecting risk aversion, then estimated discount rates will be biased upwards. Thus, the double multiple price list and the convex time budget are proposed to be the alternative methods with different approaches to address the issue of utility function curvature. Introduced by Andersen et al. (2008), the double multiple price list is implemented in two stages, in which the first stage is to identify discounting while the second stage is to identity utility function curvature through decisions on risky choice. The two stages are shown in Tables 5a and 5b below.

Table 5a: Intertemporal Multiple Price List

TODAY *and* 5 WEEKS from today			
For each decision number (1 to 6) below, decide the **AMOUNTS** you would like for sure **today AND in 5 weeks** by checking the corresponding box. *Example:* In Decision 1, if you wanted $19.00 today and $0 in five weeks you would check the left-most box. Remember to check only one box per decision!			
1.	payment TODAY … *and* payment in 5 WEEKS	$19.00 $0 ☐	$0 $20.00 ☐
2.	payment TODAY … *and* payment in 5 WEEKS	$18.00 $0 ☐	$0 $20.00 ☐
3.	payment TODAY … *and* payment in 5 WEEKS	$17.00 $0 ☐	$0 $20.00 ☐
4.	payment TODAY … *and* payment in 5 WEEKS	$16.00 $0 ☐	$0 $20.00 ☐
5.	payment TODAY … *and* payment in 5 WEEKS	$14.00 $0 ☐	$0 $20.00 ☐
6.	payment TODAY … *and* payment in 5 WEEKS	$11.00 $0 ☐	$0 $20.00 ☐

Table 5b: Holt-Laury Risk Elicitation

Decision	Option A						Option B					
		If the die reads	you receive	and	If the die reads	you receive		If the die reads	you receive	and	If the die reads	you receive
1	☐	1	15		2-10	8.31	☐	1	20		2-10	0.52
2	☐	1-2	15		3-10	8.31	☐	1-2	20		3-10	0.52
3	☐	1-3	15		4-10	8.31	☐	1-3	20		4-10	0.52
4	☐	1-4	15		5-10	8.31	☐	1-4	20		5-10	0.52
5	☐	1-5	15		6-10	8.31	☐	1-5	20		6-10	0.52
6	☐	1-6	15		7-10	8.31	☐	1-6	20		7-10	0.52
7	☐	1-7	15		8-10	8.31	☐	1-7	20		8-10	0.52
8	☐	1-8	15		9-10	8.31	☐	1-8	20		9-10	0.52
9	☐	1-9	15		10	8.31	☐	1-9	20		10	0.52
10	☐	1-10	15		-	8.31	☐	1-10	20		-	0.52

Instead of eliciting the degree of risk aversion to identify to curvature of the utility functions, according to Andreoni and Sprenger (2012), the convex time budget measures the degree of price sensitivity in intertemporal choice. Rather than choosing between ($X now, $0 later) and ($0 now, $Y later), respondents are given more options without $0 in between ($X, $0) now and ($0, $Y), as shown in Table 6. Between the two alternative methods, Andreoni et al. (2015) find that the convex time budget outperforms the double multiple price list on out-of-sample measures.

Table 6: Example of the convex time budget

TODAY *and* 5 WEEKS from today							
For each decision number (1 to 6) below, decide the **AMOUNTS** you would like for sure **today AND in 5 weeks** by checking the corresponding box. *Example:* In Decision 1, if you wanted $19.00 today and $0 in five weeks you would check the left-most box. Remember to check only one box per decision!							
1.	payment TODAY …	$19.00	$15.20	$11.40	$7.60	$3.80	$0
	and payment in 5 WEEKS	$0	$4.00	$8.00	$12.00	$16.00	$20.00
		☐	☐	☐	☐	☐	☐
2.	payment TODAY …	$18.00	$14.40	$10.80	$7.20	$3.60	$0
	and payment in 5 WEEKS	$0	$4.00	$8.00	$12.00	$16.00	$20.00
		☐	☐	☐	☐	☐	☐
3.	payment TODAY …	$17.00	$13.60	$10.20	$6.80	$3.40	$0
	and payment in 5 WEEKS	$0	$4.00	$8.00	$12.00	$16.00	$20.00
		☐	☐	☐	☐	☐	☐
4.	payment TODAY …	$16.00	$12.80	$9.60	$6.40	$3.20	$0
	and payment in 5 WEEKS	$0	$4.00	$8.00	$12.00	$16.00	$20.00
		☐	☐	☐	☐	☐	☐
5.	payment TODAY …	$14.00	$11.20	$8.40	$5.60	$2.80	$0
	and payment in 5 WEEKS	$0	$4.00	$8.00	$12.00	$16.00	$20.00
		☐	☐	☐	☐	☐	☐
6.	payment TODAY …	$11.00	$8.80	$6.60	$4.40	$2.20	$0
	and payment in 5 WEEKS	$0	$4.00	$8.00	$12.00	$16.00	$20.00
		☐	☐	☐	☐	☐	☐

Meanwhile, in matching tasks, respondents have to equate two choices that are different in timing by reporting how much they value each choice. Thus, the respondent should reveal their indifference point, allowing researchers to impute the discount rate. This method can be done with either real or hypothetical monetary outcomes. For example, in Indonesia and Ethiopia, Holden et al. (1998) ask respondents the following question:

> *"If you were told you have the choice between an amount of money today (present value PV) and the amount in one year (future value FV), how large would the amount today have to be for you to prefer it instead of the amount in one year?"*

Depending on the starting point of the answer, the follow-up questions would try to identify the point of indifference. If the initial FV starts at 100, the authors ask the respondent whether she prefers PV = 100 to FV = 100, then between PV = 90 and FV = 100, etc., until the indifference point is identified.

On the other hand, pricing tasks elicit respondents' willingness-to-pay for an outcome at a particular time, such as an extra year added to one's life. Meanwhile, rating tasks ask respondents to rate a hypothetical outcome at a specific time by its attractiveness or aversiveness. In a field survey, respondents are administered questions related to real-world behaviors that entail trade-offs between two different time horizons. While questions in survey data are based on real-life decisions, there are many other factors that are not related to time preferences but contribute to such decisions, such as the lack of information, norms, risk tolerance, etc. Thus, the discounting behaviors inferred from a field survey should be interpreted with caution (see Frederick et al., 2002 for more examples for these methods).

5. Recommendations for researchers and practitioners

This toolkit has provided details about the decision-making process of farmers in agricultural technology adoption. It has considered uncertainty – risk and ambiguity – as well as people's attitudes and preferences regarding risk, uncertainty, and patience. It has also outlined the role of forming and updating beliefs. Given the importance of these factors in the decision-making process, the following practices are recommended:

1. Measure risk-aversion, ambiguity-aversion, and time discounting – the three main attitudes or preferences that affect decision-making.
2. Measure farmers' beliefs regarding the possible outcomes of technology you are investigating.
3. Pilot the potential questions first to ensure respondents understand the questions. Gather a small number of people (who will not be in the study sample) and ask them different types of questions. Let them ask questions to clarify and then ask them questions about what they understood the questions to mean and what they considered when answering them. This practice will provide a good picture of the best questions to use under the particular context.
4. Standardize the way in which questions are asked so that the data means the same thing for each respondent. The best way to do this is to use a script.
5. Adapt the questions to the context. For example, if the word "gamble" or "lottery" invokes negative connotations, use the word "game" or another appropriate term instead.
6. When using the lab-in-the-field experiments, incentivize honest answers by involving real-stake money in at least one round of the games if possible.

Once measurements are in hand, programs and policies can be crafted accordingly. For example, if there is a high measured degree of risk-aversion, providing farmers with insurance can improve adoption. If ambiguity-aversion is prevalent, providing farmers with information regarding the probabilities can help (for example, providing farmers with information regarding the true rate of counterfeiting of herbicide in their local market). If beliefs about the benefits or of the possibility of an outcome occurring are very spread out and people are ambiguity-averse, reducing this type of uncertainty through demonstrations of the technology can be useful. The goal is for farmers' beliefs to align with reality – if a technology will be beneficial to them, the goal is for farmers to know that with as little uncertainty as possible.

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