The role of experience in climate adaptation: Evidence from a field experiment in China

Abstract

This paper extends the existing individual decision-making framework of adapting to climate change by considering the effects of prior personal experience in shaping risk preferences. Conducting Prospect Theory-based "lab-in-field" risk experiments in rural areas of Xinjiang Province, we elicit Chinese farmers' risk curvature and probability bias by adopting more flexible Prelec's two-parameter probability functions. Using Bayesian approaches to estimation, we find that farmers' prior experiences not only provide information that influences the subjective distributions of future outcomes but also, by shaping farmers' personal risk preferences, affects how farmers absorb and update this information. As such, our research suggests that individual risk preferences can evolve, and the effects of personal experience on preferences exhibit distinct patterns depending on whether farmers face benefits or losses. Experiencing production damages tends to make farmers more averse to losses and increases their optimistic bias concerning personal loss risks. A policy implication of these findings is that it is crucial to reduce farmers' cognitive biases regarding their own climate-related losses and their over-reliance on personal experiences in order to make accurate risk management decisions.

Keywords: decision-making framework; climate change; experience; Bayesian approach; risk preference

1. Introduction

Adaptation to climate change is one of the key challenges for farmers and agricultural and environmental policy makers alike. Governments, businesses, and non-governmental organisations often prefer top-down to bottom-up adaptation approaches due to advantages in speed, control, and efficiency (Qamar and Archfield 2023). However, top-down governance has not always proven to be the most effective (Nunn, Aalbersberg et al. 2014), with more recent evidence emphasising the need to integrate contributions among different actor groups in climate risk management and adaptation (IPCC 2022, Pisor, Basurto et al. 2022). These studies suggest that the effectiveness of climate change adaptation largely depends on communities' and individuals' participation, especially for farming and fishing practices and ecosystem-based adaptations. It is therefore essential for climate policymakers and researchers to understand the decision-making processes of individual farmers' climate change risk management strategies, to improve the effectiveness of efforts to tackle climate change.

Behavioural science has gained increasing attention over the past three decades for its potential to inform policy innovations and to address long-standing social problems (Bryan, Tipton et al. 2021). Climate researchers have also turned to behavioural science for insights into the cognitive processes behind human decision-making (van der Linden and Weber 2021, Whitmarsh, Poortinga et al. 2021). Expected value and utility theories provide a framework for understanding how rational choices should be made in the context of risk (Quiggin 1982). When applied to climate change adaptation, these models assume that a reasonable decision-maker evaluates the probability of a weather event and its expected impacts to choose the option that maximises benefits or minimises damages. There is a substantial body of evidence, however, that people often do not follow economists' definitions of rational action and tend to violate the assumptions of expected utility theory (Tversky and Kahneman 1979). Alternative theories, such as Prospect Theory, have emerged to better capture real-world decision-making under risk (Barberis 2013).

In an alternative strand of literature, some of studies have applied the Theory of Planned Behaviour to help design better programs for alleviating and reducing the negative impacts of climate change (Morten, Gatersleben et al. 2018, Zhang, Ruiz-Menjivar et al. 2020). This theory asserts that human intention exists before any behavior, and this intention is the consequence of attitudes toward the behaviour, subjective norms, and perceived behavioural control (Ajzen 1991). The Protection Motivation Framework, initially developed to help understanding of the impact of fear appeals on health-related behaviour (Prentice-Dunn and Rogers 1997), has also recently been used to explain and predict proactive adaptation behaviour to climate risk from the perspectives of threat appraisal and coping appraisal (Villamor, Wakelin et al. 2023).

Despite their contributions, these leading behavioural theories often overlook how experience shapes behaviour. It is not that these theories assume people do not have experiences, but rather that they either treat the experiences as implicit or alternatively as just a form of additional information. Expected Utility and Prospect Theory are mathematical frameworks. They assume that people make decisions relying on descriptive scenarios where probabilities and outcomes are given explicitly (Tversky and Kahneman 1992). How prior experience impacts on the parameters within these models is not considered. That is, in Expected Utility and Prospect Theory, prior experience may shape the probabilities that determine behaviour, but not how these probabilities are used.

The Theory of Planned Behavior assumes that behavioral attitude, subjective norms, and perceived behavioral control are the essential factors determining behavioral intention (Ajzen 2020). This theory does not account for other variables that may influence a person's behavioral motivation to perform a behavior, such as self-identity, anticipated affect, or experience (Ajzen 2020). Similar to the Theory of Planned Behavior, the Protection Motivation Theory also does not recognise the importance of prior experience. According to Protection Motivation Theory, previous experience may be a source of available information in the appraisal processes but is not considered necessary to influence behaviour (Villamor, Wakelin et al. 2023).

Recent studies have emphasised the importance of experience in shaping individual motivations and behaviours. After introducing Prospect Theory, Kahneman et al. (1997) argued that modern decision theory often ignores experience-based utility. Kahneman and Sugden (2005) wrote that the maximisation of experienced utility could be one of the normative criteria for economic analysis. Subsequent research has explored how decision-makers rely on personal experiences, particularly in the absence of clear descriptive information (Ding, Min et al. 2022). Ajzen (2020), the founder of the Theory of Planned Behaviour, also acknowledges the potential for incorporating past behaviour into the Theory of Planned Behaviour to enhance its explanatory power. Similarly, extensions of the Protection Motivation Framework have begun to integrate prior experiences. For example, Botzen et al. (2019) found that individuals with prior flood experiences were more likely to adopt mitigation measures.

Although much existing empirical research has explored farmers' risk management decision-making frameworks for responding to climate change, the evidence on the role of personal experience in shaping behavioural parameters remains limited. For example, most previous studies on how personal experience influences farmers' decisions to adapt simply verify the direct causal relationships between prior experience and adaptation decisions using regression models (Van der Linden 2015, Trinh, Rañola Jr et al. 2018, Singh, Eanes et al. 2020).

Our paper contributes to filling this research gap through two key contributions to the literature. First, we develop a decision-making framework for farmers' adaptation to climate change based on expected utility theory/prospect theory and validate our assumptions through "lab-in-field" experiments. This framework argues that leading theoretical frameworks should not remain silent on the potential impacts of farmers' subjective experiences on the cost-benefit analysis of climate change adaptation investments. The role of prior experience may not just be a form of objective information but something that shapes preferences.

Second, we empirically verify that individual risk preferences are unstable and can be affected by personal prior experience. Although some of the literature has explored how adverse shocks influence people's risk preferences, few existing studies carefully distinguish the impacts of events on individual risk preferences between negative domains and gain domains. We aim to provide evidence that the impacts of previous agricultural production losses on farmers' risk preferences vary across different domains, with a greater influence on their risk preferences in the loss domain. Our paper therefore also contributes to providing a deeper and more accurate understanding of the individual decision-making process in climate change adaptation, as well as the implications for climate change adaptation policy in the context of nudges.

The remainder of this paper proceeds as follows. Section 2 builds the conceptual framework of the individual decision-making process of climate change adaptation. In Section 3, we present the experimental design and model elicitations. The data analyses and results are displayed in Section 4. Section 5 discusses our results. Section 6 provides an extension analysis, and Section 7 concludes.

2. Conceptual Framework

In recent years, (cumulative) prospect theory has been widely applied to the study of climate adaptation, for example, in predicting individuals' risk management behaviors (Villacis, Alwang et al. 2021) and designing behaviorally informed weather insurance products (Dalhaus, Barnett et al. 2020). Prospect theory posits that individuals' decision-making under uncertainty is primarily shaped by their risk preferences and subjective expectations regarding future outcomes. As a result, most empirical studies grounded in the framework of prospect theory tend to attribute the formation of behavioral preferences primarily to individuals' subjective expectations about future outcomes, while giving relatively little attention to the role of past experiences in shaping decisions. However, both research and practical evidence suggest that individuals' adaptive decisions in response to climate risks are often strongly influenced by their prior experiences. These experiences may include accumulated farming knowledge and practices (Trinh, Rañola Jr et al. 2018), personal encounters with extreme weather or climate events (Akerlof, Maibach et al. 2013, Van der Linden 2015) or financial losses and economic disruptions caused by climate change (Singh, Eanes et al. 2020). Such experiences not only shape individuals' perceptions of future risks but may also influence their behavioral motivations and psychological responses, ultimately affecting their decision-making preferences and strategies.

The importance of experience lies partly in its role as a key source of information for forming subjective expectations. In most real-world settings, individuals make decisions in the absence of objective probabilities and therefore rely heavily on past experiences to evaluate uncertain futures. Yet the impact of experience extends beyond information provision, and it also shapes how individuals process, interpret, and apply that information, influencing decisions independently of the expectations themselves. This raises an important question: how do farmers' personal experiences of harvest losses caused by climate and weather events affect their responses to future climate change? More importantly, how can such experiences be systematically incorporated into the decision-making framework for climate adaptation to build a more behaviorally grounded and predictive model of adaptive behavior?

This study seeks to advance an integrated framework for climate risk decision-making by embedding psychological insights within the economic structure of prospect theory. In neoclassical economic models, preferences are typically assumed to be stable and exogenously given, while expectations are formed rationally based on available information (Stigler and Becker 1977), leaving limited room for the influence of subjective experience or psychological distortions. Our framework challenges this assumption by drawing on empirical psychological research that demonstrates how both preferences and expectations are shaped by individuals' prior experiences. Within the prospect theory framework, we propose that a farmer's adaptation intention is jointly determined by his expectations about future outcomes and his preference toward risk (as illustrated in Fig.1). The first grey arrow in Fig. 1 represents the first role of past experience:

Past experience contributes to expected outcome distributions (posterior information) and formulation of intention of whether and how to prepare for the future.

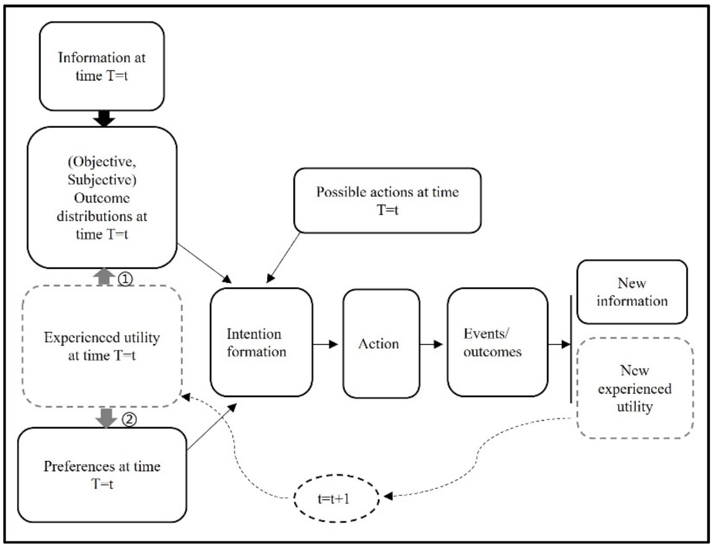

Fig. 1. The conceptual structure of the decision-making process.

Note: The figure depicts an individual decision-making framework for adapting to climate change based on Prospect Theory. The elements involved in the decision-making process are connected by solid arrows. Grey arrows and dashed lines represent the role of experience that is overlooked in both Prospect Theory and Expected Utility Theory, which is the focus of this paper.

As shown in Fig.1, this role posits that farmers' experiences related to climate change do not directly determine whether and how they engage in adaptation behaviors. Instead, these experiences influence adaptation decisions indirectly by shaping farmers subjective expectations about future prospects. This perspective contrasts with much of the existing literature, which emphasizes the direct effects of experience. For example, previous research claimed that exposure to abnormal temperatures or extreme weather events directly increases farmers' intention to adapt (Hazlett and Mildenberger 2020, Huang, Long et al. 2024). In contrast, our framework aligns more closely with the core tenets of Rational Emotive Behavior Therapy (REBT), developed by psychologist Albert Ellis. REBT posits that individuals' emotional and behavioral responses are not determined directly by activating events, but rather by their belief systems about those events (Ellis 1991). In other words, belief plays a central mediating role between experience and behavioral outcomes.

A range of psychological studies supports this "experience-belief-intention-action" pathway. On the one hand, research shows that climate-related experiences can shape individuals' beliefs and perceptions about climate change. For instance, Bergquist et al. (2019) found that people who have experienced natural disasters tend to express stronger negative emotions, such as fear, when referring to climate change, leading to heightened risk perception. Similarly, Ng'ombe, Tembo et al. (2020) reported that personal experience of climate-related production shocks significantly increase farmers' perceptions of long-term climate risks, particularly in the agricultural context. On the other hand, research in neuroscience and cognitive psychology emphasises that the brain processes factual information through subjective filters, often distorting or reconstructing the original input (Berridge and O'Doherty 2014, Bromberg-Martin and Monosov 2020). This leads to potential discrepancies between objective experiences and self-reported, subjective experiences (Howe 2021). As such, beliefs about climate change are shaped more by what people think they have experienced and how they interpret those experiences, rather than by what they actually experience.

The second role that experience may play in the decision-making process is illustrated by the second grey arrow in Fig. 1:

Farmers' exposure to extreme weather or climate shocks may lead to changes in their risk preferences, which in turn influence their adaptation intentions and behaviors. These changes in risk attitudes may manifest differently depending on whether the decision context involves potential gains or losses, resulting in asymmetric behavioral responses.

As noted earlier, prospect theory identifies risk preference as a core psychological mechanism shaping decision-making under uncertainty. While traditional economic models often treat preferences as fixed parameters, growing empirical evidence suggests that risk attitudes may shift in response to external socio-economic or natural shocks (Gächter, Johnson et al. 2022). In this line of research, researchers have employed simplified self-reported scales, income-gamble questions, or incentivized experimental designs to measure risk preferences before and after shocks, as well as longitudinal and cross-sectional data analyses to reveal heterogeneity across contexts. Existing studies yield three main strands of findings. The first group of studies suggests that shocks reduce risk aversion and thereby increase individuals' willingness to take risks. For example, Kahsay and Osberghaus (2018), using self-reported risk measures, found that German households who experienced storm damage were more willing to take risks. Similarly, Holden and Tilahun (2021), through field experiments with real monetary incentives, showed that young adults in Sub-Saharan Africa became less risk-averse after experiencing drought.

A second group of studies, by contrast, concludes that shocks strengthen risk aversion. Brown, Montalva et al. (2019), drawing on longitudinal survey data and the multiple price list method, found that households in Mexican regions with rising violent crime exhibited stronger risk aversion. Reynaud and Aubert (2020), in a randomized field experiment in Vietnam, also demonstrated that villagers recently exposed to flooding were more risk-averse than those in comparable unaffected villages. Finally, a third set of studies highlights the stability of risk preferences. Sahm (2012), using a large-scale panel survey of older Americans and the simple hypothetical income gamble method, showed that personal events such as job loss or divorce did not significantly alter individuals' willingness to take risks. Likewise, Drichoutis and

Nayga Jr (2022), in a longitudinal incentivized experiment with Greek undergraduate students, found that even in the face of the severe public health and economic disruptions caused by the COVID-19 pandemic, students maintained stable risk preferences over time.

Despite these findings, most empirical studies on the impact of shocks on risk preferences have focused predominantly on the gain domain, with relatively limited attention to the loss domain (Brown, Montalva et al. 2019, Meier 2022). This imbalance raises two important concerns. First, both theoretical and empirical literature widely acknowledge that individuals exhibit distinct risk preferences in gain versus loss contexts. For example, decision neuroscience research suggests that emotional responses are triggered by different neural mechanisms in these two domains (Levin, Xue et al. 2012), and prospect theory itself posits that individuals tend to be risk averse when dealing with gains but risk seeking when facing losses (Tversky and Kahneman 1992). Accordingly, environmental shocks may exert opposing effects on risk preferences depending on the domain (Reynaud and Aubert 2020). Second, the effects of negative shocks on risk preferences in the loss domain may be especially pronounced and psychologically salient, yet this dimension remains largely underexplored in the existing literature. Moreover, disaggregating risk preferences into distinct components such as utility curvature, probability weighting, and loss aversion, allows for a more nuanced detection of subtle changes in individuals' risk attitudes in response to external shocks. In response to these gaps, we extend our prospect theory-based framework of climate adaptation by explicitly modeling the second role of experience. This extension captures the domain-specific heterogeneity and asymmetry in how prior experiences shape individuals' attitudes toward risk.

In summary, building on this rich literature, our study advances a framework that emphasises the indirect role of experience in shaping adaptation. Rather than acting as a direct trigger of adaptive behaviour, experience operates through cognitive mechanisms by influencing climate beliefs and risk preferences, which subsequently shape farmers' willingness and decisions to adapt. We conceptualise adaptation as a multi-stage decision-making process. Farmers first form expectations about future climate outcomes based on prior experiences, and these expectations together with risk preferences determine whether and how adaptation strategies are adopted. Although the empirical analysis does not directly observe adaptation behaviours, it focuses on these critical antecedents as highlighted by prospect theory, thereby elucidating the pathways through which experience informs adaptation decisions and extending existing behavioural models of climate change adaptation.

3. Materials and methods

3.1. Lucky wheel games[1] design and implementation

This section presents the lab-in-the-field experiment framework. Elicitation techniques for measuring individual-specific risk preference are mainly divided into three categories: multiple price lists (Holt and Laury 2002), self-assessment questions (Dohmen, Falk et al. 2011), and hypothetical gambles based on non-monetary questions (Anderson and Mellor 2009). This study tailored the multiple price lists and designed experiments for individuals based on the standard format originated by Binswanger (1980) and popularised by Holt and Laury (2002). The experimental design has a total of four groups, including positive, negative, and mixed prospects (Shown in Appendix B, Table B1). In the experiments, people were shown ten different binary-choice lottery games. In each game, they were required to pick either the "risky" option or the "safe" option. These two options are different in expected payoffs.

This research designed "Lucky wheel" games as visual aids to help participants understand the process of the whole experiment. The primary reasons for designing the lucky wheel and the money bag as mechanisms to communicate with farmers was twofold. First, local farmers have lower average education levels (seven to nine years in this research) and limited mathematical education. Using reward mechanisms commonly known to local farmers in China's marketing venues is more vivid and easily understandable to them compared to merely presenting multiple price lists. Second, as shown in Appendix B, Table B1, the risk options in our designed multiple price lists have three different outcomes. By changing the area range of the cards with three colours attached to the lucky wheel, the probabilities of the three outcomes could be rapidly altered on-site.

To increase the accuracy of the collected data, every participant was required to complete a practice game before the formal experiment began. A pilot experiment is an essential preliminary step to ensure the feasibility of the research design. It helps verify that participants fully understand the rules and that the data collection procedures run smoothly, thereby enhancing the internal validity of the experiment (Van Teijlingen and Hundley 2001, Croson 2002). In this practice session, researchers carefully explained the rules and guided participants through the payoff structures involving gains, losses, and probabilities. Participants were encouraged to ask questions and were asked to restate the game mechanics in their own words.

[1] Lucky Wheel Game is the name of the experiment and was specifically designed for conducting fieldwork in China.

The formal experiment began only after confirming that participants had fully understood the tasks.

In the formal games, farmers were given the option to either spin the wheel or take the money bag. The rewards from the lucky wheel depended on where the pointer stayed. For example, in the case of “Game 1” illustrated in Fig. 2, if a farmer chose the lucky wheel, he had a 50% probability of losing 7 yuan, a 45% probability of gaining 7 yuan, and a 5% probability of losing 0 yuan. Conversely, if a farmer chose the money bag, he would incur a certain loss of 1.5 yuan. The game in Fig. 2 has negative expected payoffs, however, other games have positive and zero expected payoffs (Shown in Appendix B, Table B1).

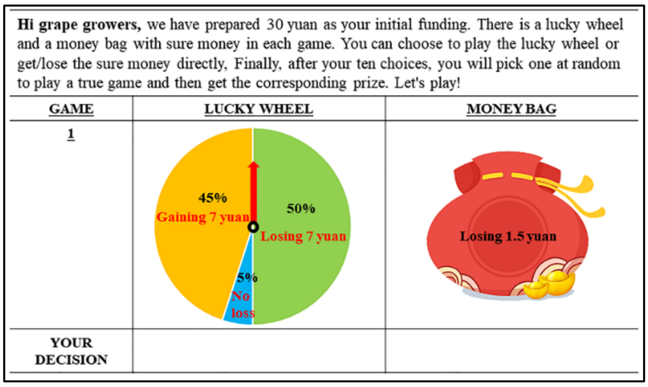

Fig. 2. Example of a lucky wheel game.

It is important to remember that each farmer plays ten different binary-choice lottery games. Figure 2 shows only one of these games here due to the space limitations. For this specific game, shown in Figure 2, researchers told the players: if you choose the lucky wheel, you will have a 50% chance of losing 7 yuan, a 45% chance of gaining 7 yuan, and a 5% chance of losing 0 yuan. Conversely, if you choose the money bag, you will incur a certain loss of 1.5 yuan. Will you choose the lucky wheel or take the money bag?

Existing literature suggests that participants find it hard to imagine how they would actually behave when they face hypothetical choices. The measurements of individual risk aversion show differences under hypothetical and actual incentives (Hackethal, Kirchler et al. 2023). However, many studies in social sciences, most prominently psychology, used hypothetical lottery questions rather than actual monetary incentives to elicit individual risk preferences. To minimise hypothetical bias and encourage truthful responses, we informed participants that after completing ten hypothetical decision tasks on the questionnaire, they would randomly draw a number from a box containing notes labelled 1 to 10. The number drawn determined which of the ten games would be played for real monetary rewards. Given the time constraints and cognitive burden of rural participants, incentivizing all ten decisions would have significantly increased the cost and complexity of the field experiment. To strike a balance between incentive compatibility and practical feasibility, we adopted a random lottery incentive system (RLIS), in which only one of the ten decisions was randomly selected for actual payment. A substantial body of literature has demonstrated the validity of this approach and provided evidence that "pay one" and "pay-all" designs yield broadly comparable results (Cubitt, Starmer et al. 1998, Charness, Gneezy et al. 2016, Clot, Grolleau et al. 2018). Before the real game, each participant was provided with 30 yuan to prevent them from losing their own money. The post-experimental analysis showed that the average payoff that farmers actually got to take home was 29.53 yuan, which already accounts for the initial 30 yuan.

3.2. Study area and data collection

The study area is in the Xinjiang Uygur Autonomous Region, which has complex ecological and geographical conditions and a climate that differs from other parts of China (Yao, Chen et al. 2021). Meteorological research reports that the increased interannual variability of precipitation and extreme precipitation events make a major contribution to the warming-wetting trend in Xinjiang (Wang, Zhai et al. 2020), which is the most important grape-producing region, with the largest output and planted areas among all the provinces (National Bureau of Statistics, 2021). The warmer and wetter climate trend has brought particular challenges to the agricultural risk management of grape cultivation and production. According to governmental statistics, the grapes in Turpan have frequently suffered from natural disasters such as strong winds, heavy rainfall, and hail. The average annual affected area was nearly 3333 ha, and the cumulative economic damages reached 1.1 billion yuan from 2013 to 2020 (Kang 2023).

We selected Liushuquan town as our study site for three main reasons. First, climate records from 1951 to 2021 show a marked rise in both the frequency and total amount of rainfall during the grape harvest period (as shown in Appendix C, Fig. C1), making Liushuquan a climate-sensitive location that is well suited to our analysis. Second, grapes are the dominant cash crop and the primary source of household income, yet they are highly susceptible to rainfall-induced diseases, creating strong incentives for adaptation. Thirdly, the local government actively promotes the adoption of rain covers and provides subsidies, embedding our study within a real-world policy environment.

Data was collected from local grape growers from April to June 2019. We conducted a preliminary investigation in April 2019 to verify the rationality and understandability of our questionnaires. The pilot research was conducted through a focus group of three local farmers and a village head. The formal survey started in May 2019. All documents related to the game were translated into Chinese. With the help of the village heads, researchers obtained a list of local grape growers and their contact information. We randomly selected farmers from the roster and each farmer was selected with equal probability. Then, the village heads helped us to contact the selected farmers. Participants came to the experimental site and spent about 40 minutes playing the "Lucky Wheel" game and finishing an anonymous demographic questionnaire. Finally, we deleted questionnaires that were not fully completed and obtained 155 valid observations.

The study received ethical clearance from XX [reference number] (to be made publicly available after the paper is accepted). Prior to participation, all respondents were fully informed of the purpose of the study, the voluntary nature of their involvement, and their right to withdraw at any stage without penalty. Given the potentially sensitive political context of the study region, particular care was taken to safeguard respondents' privacy and autonomy. Specifically, enumerators received systematic training to avoid leading questions during interviews. All interviews were conducted in private settings to ensure confidentiality. For sensitive items such as age and income, the questionnaire was designed with categorical options rather than requiring exact figures, and no personally identifiable information was collected or recorded. These safeguards ensured that all respondents provided informed consent to participate freely, without coercion or undue pressure.

3.3. Demographic description

Sample characteristics are displayed in Appendix B, Table B2. Nearly half of respondents are between 40 and 50 years old. The gender ratio is roughly balanced, with 47.7% female. 72.9% of farmers have not received education beyond high school. Almost all the respondents believe they do not have poor health. The largest proportion of annual income of a family is between 30,000 and 50,000 yuan. Compared to agricultural income, off-farm income among farmers in Xinjiang is relatively low, with more than half of the households (54.8%) earning less than 2,000 yuan annually from non-agricultural sources, indicating that agriculture remains their primary source of income. Most of the respondents are experienced grape farmers, with just three farmers having less than three years of planting experience, whilst nearly half have 10 to 20 years. 77.4% of households included two people who worked on the family farm.

3.4. Measuring risk preference parameters

From an economic perspective, the "Lucky Wheel" game for a person is essentially a comparison between the utility of choosing the risky payoff from the lucky wheel (LW) and the utility of choosing the certain payoff from the money bag (MB). When farmers think the utility of playing the lucky wheel (U_{LW}) is greater than the utility of taking the money bag (U_{MB}), they choose to spin the lucky wheel. To model farmers' binary choice between the lucky wheel and the money bag, we adopt a logit choice model grounded in Random Utility Theory (Azari, Parks et al. 2012). In this model, the utility associated with each option has two parts: a deterministic component, represented by the expected utility, and a stochastic component, capturing unobserved factors. In addition, we assume that the error terms are independently and identically distributed with a Type I Extreme Value distribution, which leads to a logistic formulation of the choice probability. The probability that individual i prefers LW to MB is assumed to be:

$$Pr_i(LW \succ MB) = 1 \Big/ 1 + exp^{-\theta_i(EU_{LW_i} - EU_{MB_i})} \tag{1}$$

Where EU_{LW_i} is the expected utility of choosing the LW option. EU_{MB_i} is the expected utility of choosing the MB option. θ_i is the scale parameter governing the individual's sensitivity to differences in expected utility. We restrict θ_i to be positive (as shown in Appendix A, Text A1), as a positive value ensures that higher expected utility leads to a higher probability of being chosen, which aligns with economic intuition.

We chose the logit model over the probit model for three reasons. First, the logit model assumes a logistic distribution for the error term, which closely resembles the normal distribution assumed in a probit model. Unlike the probit, however, the logit provides a closed-form expression for the choice probability, making it more convenient for computation, especially in a Bayesian setting (Aldrich and Nelson 1984). Second, the logit model is widely used in behavioural and experimental economics due to its interpretability and ease of integration with latent parameter structures such as individual-level heterogeneity in decision sensitivity (Krueger, Bierlaire et al. 2021). Third, the logistic distribution has heavier tails than the normal distribution, making the logit model more robust to extreme values and better suited to experimental data, where occasional large utility differences may occur (Aldrich and Nelson 1984).

The observed choices are defined $y_i = 1$ if LW is chosen, and $y_i = 0$ if MB is chosen. The prospect of two options can be expressed in the form:

$$Prospect = (X, P) \tag{2}$$

In the above form, X denotes the payoffs and $X \sim (x_1, x_2, \cdots, x_n)$. P represents the corresponding probabilities and $P \sim (p_1, p_2, \cdots, p_n)$. n refers to the number of payoffs in each option.

In this paper, we estimate the expected utilities of the two options using standard expected utility theory (EUT) and prospect theory (PT). By comparing different risk preference models, we aim to provide empirical evidence on which decision theory better characterises people's risk-taking behavior, while also striving to obtain the most accurate risk preference parameters. In the experiment, payoffs in each option are in the mixed domain (both positive and negative). There were *m* negative values and *n-m* positive values, and we ranked all the values from worse to better. Therefore, the prospect utility of each option can be specified as follows:

$$PU_i = \sum_{t=-m}^{n-m} v(X_{it})\pi(P_{it}) = \sum_{t=-m}^{0} v^-(X_{it})\pi^-(P_{it}) + \sum_{t=0}^{n-m} v^+(X_{it})\pi^+(P_{it}) \tag{3}$$

Extensive literature exists exploring the more appropriate parametric specifications of value functions and weighting functions. The extent of individual psychological deviation from payoffs and probabilities can be well described by power value curves (Stott 2006, Balcombe and Fraser 2015) and asymmetric S-shaped curves (Fehr-Duda and Epper 2012). So, we adopt the power value function from Tversky and Kahneman (1992), which is expressed as follows:

$$v(X_{it}) = \begin{Bmatrix} v^+(X_{it}) = {X_{it}}^{\alpha_i}\ if\ X_{it} \geq 0, \alpha_i > 0; \\ v^-(X_{it}) = -\lambda_i(-X_{it})^{\beta_i}\ if\ X_{it} < 0, \beta_i > 0; \lambda_i > 0. \end{Bmatrix} \tag{4}$$

Where $v(X_{it})$ is the value function. t refers to the tth number of payoffs in each option. The decision weights for gains and losses are calculated by separate capacities:

$$\pi(P_{it}) =$$

$$\begin{Bmatrix} \pi^+(P_{i(n-m)}) = w^+(P_{i(n-m)}) \\ \pi^-(P_{i(-m)}) = w^-(P_{i(-m)}) \\ \pi^+(P_{it}) = w^+(P_{it} + \cdots + P_{i(n-m)}) - w^+(P_{i(t+1)} + \cdots + P_{i(n-m)})\ if\ 0 \leq t \leq n-m-1 \\ \pi^-(P_{it}) = w^-(P_{i(-m)} + \cdots + P_{it}) - w^+(P_{i(-m)} + \cdots + P_{i(t-1)})\ if\ 1-m \leq t \leq 0 \end{Bmatrix} \tag{5}$$

Here, $\pi(P_{it})$ represents the decision weight. The functions $w^+(.)$ and $w^-(.)$ are the weighting functions for the gain and loss domains, respectively. Both functions are strictly increasing and continuous, with $w^+(0) = w^-(0)$= 0 and $w^+(1) = w^-(1)$ = 1.

We use the Prelec probability weighting function to model how people subjectively perceive probabilities, incorporating both Prelec's one-parameter probability weighting function (Prelec I,$w(P)= exp^{(-(-lnP)^{\delta})}$) and the more flexible two-parameter version (Prelec II, $w(P)= exp^{(-\gamma(-lnP)^{\delta})}$). Compared with Prelec I, Prelec II not only satisfies all the target properties of decision weights but also offers greater flexibility, avoiding the constraint of the inflection at $^{1}/_{e}$ (Prelec 1998). Specifically, the forms of the weighting functions are defined as:

$$\text{Prelec I: } w(P_{it}) = \begin{cases} w^{+}(P_{it}) = exp^{(-(-\ln(P_{it}))^{\delta_i})}, \gamma_i > 0; \delta_i > 0 \\ w^{-}(P_{it}) = exp^{(-(-\ln(P_{it}))^{\eta_i})}, \xi_i > 0; \eta_i > 0 \end{cases} \tag{6}$$

$$\text{Prelec II: } w(P_{it}) = \begin{cases} w^{+}(P_{it}) = exp^{(-\gamma_i(-\ln(P_{it}))^{\delta_i})}, \gamma_i > 0; \delta_i > 0 \\ w^{-}(P_{it}) = exp^{(-\xi_i(-\ln(P_{it}))^{\eta_i})}, \xi_i > 0; \eta_i > 0 \end{cases} \tag{7}$$

Where the free parameters α_i, λ_i, β_i, γ_i, δ_i, ξ_i, η_i govern the shape of value functions and weighting functions.

An important drawback of the multinomial logit is that the choice sets have to comply with the "Independence from Irrelevant Alternatives" (IIA) property (Hausman and McFadden 1984). This property means that the relative probabilities of choosing any two alternatives are unaffected by the attributes of other alternatives in the choice set (Hausman and McFadden 1984). However, in terms of our "Lucky Wheel" games above, the unobservable components of alternatives are not completely independent and identically distributed. As Appendix C, Fig. C2, the event that person one plays game one and chooses option one is not independent of the event that person one plays game ten and chooses option one because both events are determined by this person's preferences and traits. Meanwhile, individual heterogeneity may lead the estimated variables not to have the same probability distribution.

To relax the IIA limitation, we estimate our models using a hierarchical Bayesian framework, which can be described in a similar way to the hierarchical mixed logit model. One advantage of using Bayesian estimation for risk preferences is that it can provide more precise estimates by pooling prior beliefs over plausible risk preferences, especially when it is unclear which choice tasks or models are best suited for inference (Gao, Harrison et al. 2023). Another benefit is that hierarchical Bayesian logit can estimate risk preferences at the individual level (Fraser, Balcombe et al. 2021), and these results will be used in subsequent empirical models. In hierarchical Bayesian inference, it is essential to explicitly and thoroughly specify both priors and hyperpriors for the parameters to be estimated to ensure a clear model specification. Detailed information about the priors and hyperpriors in the risk preference model is provided in the Appendix Text A1. All joint posterior parameter distributions are inferred using Hamiltonian Monte-Carlo (HMC) and its extension the No-U-Turn Sampler (NUTS). Compared with traditional Markov Chain Monte Carlo simpler methods, such as Gibb's sampling or random-walk Metropolis, an essential advantage of HMC is its improved computational speed and efficiency, especially in higher-dimensional and more complex models (Thomas and Tu 2021). HMC needs an optimal number of steps and a step size, and the gradient of the log-posterior via a "mass matrix" (Hoffman and Gelman 2014). NUTS can automatically generate nearly optimal number of steps and tune the desirable step size parameter during the warm-up phase, while stan can fast and accurately accomplish gradient calculations with automatic differentiation (Monnahan and Kristensen 2018). The models in this paper were implemented in Pystan. The posterior inference was based on 8,000 samples, and the first 24,000 samples were discarded in the warm-up phase. The RHAT convergence stats were all less than 1.1, which showed that all models converged well.

3.5. Empirical models for the role of experiences

As we proposed in the conceptual framework, the pleasure and pain from experiences are likely to influence how people evaluate their experiences and thus form their expectations for the future. In our research context, we assume that people's beliefs about future climate conditions are heterogeneous, influenced by their past losses from weather events. To explore the possible relationship, this research builds the following model:

$$Y_i = \alpha + \rho_1 X_i + \sum_{n=2}^{6} \rho_n CV_{in} + e_i, \tag{8}$$

Where Y_i as the explained variable refers to the ith respondent's anticipated average number of rainy days during the grape harvest (from July to September). X_i is the ith farmer's subjective loss experience that is the proxy of experience utility. We asked respondents to provide information about the loss rate of grape profit due to the rain between July and September in the previous year. CV_{in} are control variables that help to separate the effects of variables that are not of primary interest, such as gender, the years of living in Hami city, education, vineyard location and ease of hiring workers. α is the intercept. The error e_i satisfies the normal distribution N(0,100). ρ_1 and ρ_n are the coefficients to be estimated. We specify Normal posterior distributions for ρ_1 and ρ_n ($\rho_1, \rho_n \sim N(0,5)$) because we believe the influences of loss experience and control variables on farmers' beliefs are positive or negative and the means are zero. n is the number of control variables.

Because this research proposes that individual risk preferences at a specific time are determined by the comprehensive feelings brought about by experiences, we include seven risk preference parameters and self-reported losing experiences in our models:

$$y_i^{\rho} = \pi + \varphi_1^{\rho} X_i + \sum_{n=2}^{6} \varphi_n^{\rho} CV_{in} + e_i, \tag{9}$$

Where y_i^{ρ} are individual risk preference parameters and $\rho = 1,2,3 \ldots 7$. y_i^{ρ} refers to risk aversion for gains (α_i), risk aversion for losses (β_i), loss aversion (λ_i), sensitivity to probability in the gain domain (δ_i), sensitivity to probability in the loss domain (η_i), attitudes to the largest gains (γ_i) and attitudes to the largest losses (ξ_i). CV_{in} are control variables that were selected mainly based on factors of influencing risk preferences discussed in the literature. CV_{in} includes age (Schildberg-Hörisch 2018), gender (Falk, Becker et al. 2018, Ayton, Bernile et al. 2020), income, education (Chuang and Schechter 2015), and also health status. φ_1^{ρ} and φ_n^{ρ} are the coefficients to be estimated. The priors are set as Normal distributions ($\varphi_1^{\rho}, \varphi_n^{\rho} \sim \mathrm{N}(0,5)$) since we assume the probability distributions of the influences of experience and control variables on risk preferences are symmetric about the mean zero. π is the intercept. e_i is the error term and satisfies $e_i \sim N(0,100)$. It is worth noting that, given the cross-sectional nature of our data, our empirical strategy can only identify heterogeneity. Nonetheless, we interpret systematic differences observed across individuals with varying loss experiences as indicative of potential dynamic patterns in risk preferences.

We also adopt the Bayesian approach to estimate the parameters. This technique is a more direct or natural technique to answer a research question since it estimates the parameter of interest directly from the computed population distribution instead of estimating from the sampling distribution as for the frequentist approach (Hespanhol, Vallio et al. 2019). The reasons are as follows. First, the valid observations of this study are 155. Frequentist methods, such as ordinary least squares and maximum likelihood estimation, require large, repeated samples from the population (Wooldridge 2016). Small sample sizes are considered likely to lead to model overfitting, as well as noisy and unreliable estimates (Alam, Georgalos et al. 2022). Bayesian inference could help mitigate the above drawbacks and provide valid estimations in both large and small samples (Chernozhukov and Hong 2004).

Second, Bayesian techniques allow researchers to incorporate background knowledge into their statistical models instead of testing the null hypothesis and ignoring the lessons of previous studies (Van de Schoot, Kaplan et al. 2014). Third, compared with the assumed fixed parameters for the frequentist, Bayesian inference concerns that all unknown parameters are treated as uncertain and random (Lancaster 2004). We can get the probability distribution of the parameters of interest by the Bayesian statistics. The variance of the prior distribution captures the uncertainty, and the larger the variance, the greater the uncertainty (Van de Schoot, Kaplan et al. 2014).

Finally, the dependent variable Y is an ordinal categorical variable, distributed across four intervals: 1 to 2 days, 3 to 4 days, 5 to 6 days, and 7 to 8 days. This study therefore applies the Bayesian ordered logit method to regress the above equation (7). Some previous research where the dependent variable is an ordinal categorical variable also uses this approach (Chen, Zhang et al. 2016, Oviedo-Trespalacios, Afghari et al. 2020). In addition, we adopt Bayesian linear regression to deal with equation (8). The posterior inference was based on 10000 samples, discarding the first 15000 samples in the warm-up phase. The RHAT convergence stats were close to 1, which showed all the chains have converged to the posterior.

3.6. Sample size

According to the law of large numbers and the central limit theorem, frequentist statistics holds that larger samples yield more reliable inferences (Anderson, Doherty et al. 2008). Yet under limited sample conditions, frequentist inference is often constrained, reducing the robustness and credibility of results. To address this limitation, we employ Bayesian statistical methods, which are well-suited to small samples. A growing methodological literature shows that Bayesian estimation outperforms maximum likelihood estimation in small sample contexts (Etzioni and Kadane 1995, McNeish 2016, Miočević, MacKinnon et al. 2017, Ulitzsch, Lüdtke et al. 2023). Several studies published in leading journals have also relied on comparable sample sizes and successfully applied Bayesian models, yielding robust and credible findings (e.g., 90 subjects in Balcombe and Fraser 2015; 111 subjects in Gao, Harrison et al., 2023; 143 subjects in Balcombe and Fraser 2025). Importantly, the issue of limited sample size is widespread. Many studies in psychology, social science, and experimental economics rely on samples of 30-100 participants, making small samples a pervasive challenge rather than an anomaly (Russell 2002, Fraley and Vazire 2014, Schuster, Kaiser et al. 2021, Williams, FitzGibbon et al. 2025).

The strength of Bayesian methods lies in their foundation. Unlike frequentist approaches that depend on asymptotic theory, Bayesian analysis treats data as fixed and parameters as random, with inference based on the posterior distribution. In practice, sampling-based methods such as Markov chain Monte Carlo (MCMC) yield accurate inference even with small datasets, as precision depends on the number of draws rather than the sample size (Rupp, Dey et al. 2004). This eliminates the need for finite-sample corrections, delivers interval estimates directly from posterior percentiles (Zyphur and Oswald 2015, Van de Schoot, Depaoli et al. 2021), and avoids the convergence and derivation difficulties of maximum likelihood estimation in limited samples (Efron 2012). These features make Bayesian methods a robust and flexible tool for empirical research under the sample size constraints common in the social sciences.

4. Results

4.1. Risk preference model evaluation

We begin by identifying the best-performing model among five risk preference models. These models are designed to choose between expected utility theory and prospect theory, as well as to select among different prospect theory functionals. This process primarily involves testing the asymmetry of the risk coefficients in the gains and losses, and choosing between distinct probability weighting functions. This paper uses the Watanabe-Akaike information Criterion (WAIC) to compare the fit of each model. WAIC is a model selection criterion particularly well-suited for Bayesian models, with lower WAIC values generally indicating a better fit to the data (Vehtari, Gelman et al. 2017).

Based on the WAIC values of the five risk preference models presented in Table 1, several key findings can be drawn. First, PT is not always superior to EUT in describing individual risk decision-making. Specifically, the WAIC value of EUT is lower than those of PT1 and PT3 but higher than those of PT2 and PT4. This finding suggests that while EUT provides a better fit than PT models that assume symmetric risk sensitivity between gains and losses, it is outperformed by PT functionals that incorporate asymmetric risk sensitivity.

Second, a comparison of different PT specifications, such as PT1 versus PT2 and PT3 versus PT4, reveals that models allowing for asymmetric risk sensitivity (PT2 and PT4) more accurately capture participants' risk preferences than those enforcing symmetry (PT1 and PT3). Furthermore, comparing PT1 with PT3 and PT2 with PT4 demonstrates that two-parameter probability weighting models, which account for individuals' varying attitudes toward extreme gains and losses, provide a better fit than one-parameter probability weighting models. Finally, PT4 emerges as the best-performing model among all candidates, indicating that a PT framework incorporating asymmetric risk preferences and a two-parameter probability weighting function offers the most precise representation of individual risk decision-making behaviour.

Table 1

WAIC values for competing risk preference models.

Competing Models	WAIC Values
EUT: Symmetry ($\alpha_i = \beta_i$; $\lambda_i = 1$) + Linear probability ($\gamma_i = \delta_i = \xi_i = \eta_i = 1$)	1895.81
PT1: Symmetry ($\alpha_i = \beta_i$) + Prelec I ($\gamma_i = \xi_i = 1$)	2006.12
PT2: Asymmetry ($\alpha_i \neq \beta_i$) + Prelec I ($\gamma_i = \xi_i = 1$)	1796.25
PT3: Symmetry ($\alpha_i = \beta_i$) + Prelec II	2005.43
PT4: Asymmetry ($\alpha_i \neq \beta_i$) + Prelec II	1738.24*

Note: * indicates the best-performing model.

4.2. Farmers' risk curvatures and probability distortions

Next, we analyse individuals' risk preferences based on the optimal model PT4 selected in the previous section. We present farmers' degree of risk aversion and loss aversion for both positive and negative domains in Table 2. The means of α, β, λ are 0.89, 0.91 and 1.83, respectively. Using these average parameters, we plot the farmers' value function. For the average participants, the value function is concave in the positive prospects and slightly convex in the negative prospects (Fig. 3). The risk aversion parameters for Xinjiang farmers are quite close to some existing findings with the same estimation approach. For example, Ackert, Deaves et al. (2020) identified the median value of α as 0.86 for American students. But, previous research suggests that our estimates are higher than those of farmers in other countries: 0.33 for American crop producers (Zhao and Yue 2020), 0.51 for South Africa farmers (Villacis, Alwang et al. 2021), and 0.61 for Belgian apple and pear growers (Bonjean 2023). These results suggest that Xinjiang grape growers tend to be risk averse for gains and risk seeking for losses, but they are less risk averse for gains and less risk seeking than farmers in other countries.

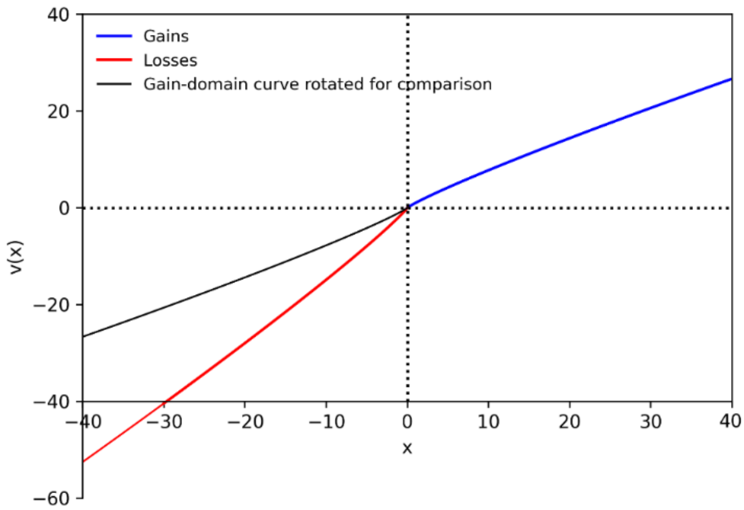

Fig. 3. Risk curvatures for gains and losses.

Note: According to the calculations of this study, the extent of individual psychological deviation from objective payoffs can be described by power function v(x)=x^0.89, for x≥0, and v(x)=-1.83*(-x)^0.91, for x<0.

Table 2

Hierarchically estimated posterior risk parameter results.

Parameter	Description	Mean	Standard Deviation
α	Measuring the degree of risk aversion/seeking for gains: α<1 risk aversion; α =1 risk neutral; α>1 risk seeking.	0.89	0.08
λ	Measuring the loss aversion:λ<1 loss seeking; λ =1 equal weighting of losses and gains; λ>1 loss aversion.	1.83	0.30
β	Measuring the degree of risk aversion/seeking for losses: β<1 risk seeking; β =1 risk neutral; β>1 risk aversion.	0.91	0.06
γ	The weighting of the largest gains: γ<1 optimism; γ>1 pessimism.	0.87	0.10
δ	Sensitivity to probability in the gain domain: δ<1 "*IS*"; δ>1 "*S*".	0.88	0.11
ξ	The weighting of the largest losses: ξ<1 pessimism; ξ>1 optimism.	1.12	0.06
η	Sensitivity to probability in the loss domain: η<1 "*IS*"; η =1 linear; η>1 "*S*".	1.03	0.06

Note: The descriptions of parameters were concluded from the studies of Tversky and Kahneman (1992) and Prelec (1998). Bayesian mixed logit model is the estimation method.

The mean of λ is equal to 1.83, which, being greater than one, implies that on average individuals are likely to be averse to losses. Our estimate of λ is somewhat lower than the values of 2.25 reported in the seminal cumulative prospect theory paper by Tversky and Kahneman (1992). Part of the possible explanation for the smaller loss aversion may be that in our experiment, farmers' losses came from the initial funding provided by the researchers, not from their own assets. Thus, farmers may show less sensitivity to the losses.

Meanwhile, we reveal farmers' nonlinearity of preferences to probabilities. γ and δ capture the subjective distortion of given probabilities in the gain prospect. γ is 0.87 below one, which suggests that farmers are optimistic and tend to overweigh the probability of the largest benefits. δ is 0.88, which suggests an inverse *S*-shaped weighting function (Table 2).

The results can be represented in graphical format, as in Fig. 4, in which the 45-degree line represents where the actual probabilities *P* are equal to transformed probabilities *W(P)*. On average, grape growers tend to overweight small and medium probabilities and slightly underweight large probabilities when they have the chance to get benefits.

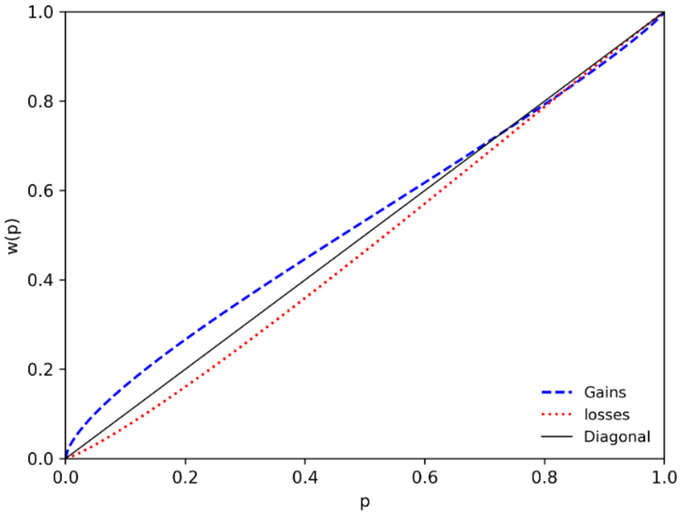

Fig. 4. Probability distortions for gains and losses.
Note: This figure shows how farmers systematically distort the objective probabilities when assessing risks. The diagonal line represents the situation where farmers do not exhibit any cognitive bias. The blue and red dashed lines represent farmers' subjective perceptions of the probabilities for gains and losses, respectively.

ξ and η control the shape of weighting functions in the loss prospect. The estimated values of ξ and η are 1.12 and 1.03 (Table 2). These estimates are different from most of the previous studies, which find the probability distortion parameters in the loss domain to be below one and the shape of weighting functions in the loss prospect to be inverse *S*-shaped (Abdellaoui, Vossmann et al. 2005, Gurevich, Kliger et al. 2009). The profile in our study is a convex curve below the diagonal. These results suggest that on average respondents exhibit optimism in the negative prospects, suggesting that they are likely to underestimate the probabilities of already suffered losses or anticipated losses.

4.3. The impact of experiences on anticipated rainfall distributions

This section explores one of the roles that experience plays in risk management decisions: that is, whether farmers' experiences of agricultural revenue shocks caused by weather events influence their beliefs about the future climate and weather distributions. We focus on the negative impacts of the upward trend in precipitation and unexpected rainfall on grape production. As outlined in the conceptual framework, "experience" can take various forms, such as farming experience, the experience of adopting adaptation measures, and the experience of losses caused by climate change. To simplify the analysis, this study focuses on one type of experience "farmers' subjective profit losses" as a proxy for experienced utility. We obtained farmers' past losses from the rain by asking: "How severe were your vineyard lost revenues from the rain during harvest season last year?" The self-reported losses by around two thirds of the respondents were between 11% and 50%, with around one fifth of respondents reporting losses of over 50% (Fig. 5). As such, it is reasonable to conclude that in the previous year, precipitation during the harvest season severely negatively affected the livelihoods of local grape growers. To assess the reliability of farmers' self-reported data, we examined the correlation between reported losses and grape income per unit of land. We find a statistically significant negative relationship (Pearson correlation coefficient = -0.34, $p < 0.01$), consistent with the economic intuition that greater losses reduce income. This provides indirect evidence supporting the validity of farmers' responses.

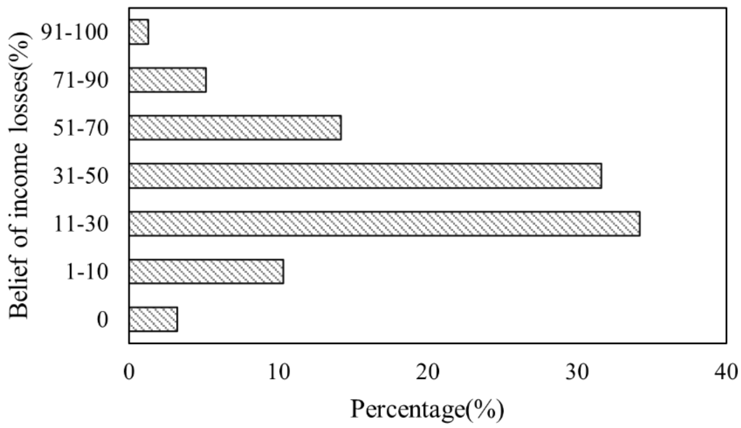

Fig. 5. Distributions of subjective severity of the rain.

Note: This figure illustrates farmers' income losses due to the rainfall during the harvest season. The data were collected from a 2019 field survey conducted in Xinjiang, China. The researchers asked farmers: how severe were your vineyard lost revenues from the rain during harvest season (July to September) last year?

Building on previous studies, we employ credible intervals to conduct Bayesian inference. In Bayesian statistics, credible intervals represent the range of values within which the true parameter is likely to fall, given the data and prior information. This is conceptually different from the confident interval used in frequentist statistics, which reflects the range of values within which the true parameter would lie with a certain probability if the experiment were repeated many times. Therefore, the significance of the regression coefficient can be assessed by examining whether the credible interval contains zero. If zero is outside the interval, we interpret the coefficient as significantly different from zero. Conversely, if the credible interval includes zero, we cannot confidently reject the null hypothesis. This method offers a more direct and intuitive interpretation of parameter uncertainty (Tiffin and Balcombe 2011, Anglim and Wynton 2015, Zyphur and Oswald 2015).

We were interested in whether farmers' expectations of future rainfall distribution differ across levels of production losses. Table 3 displays the posterior mean results of the Bayesian ordered logit model. Importantly, the posterior mean result of the impact of production damage experience on the expected number of rainy days is 0.78 with a 95% credibility interval (95% CI) of 0.47-1.08. The lower and upper bounds of the credibility interval indicate that there is a 95% chance that the impact of damage experience is between 0.47 and 1.08. Because the 95% CI does not contain the null effect, we can be 95% confident that farmers' prior rainfall production shocks do indeed influence their subjective expectations of future rainfall frequency. Specifically, respondents that have experienced more crop damage from rain in the past are more likely to believe there will be more rainy days in the future. In addition, previous studies show that beliefs about the trend of climate change and the severity of its consequences directly influence adaptation intentions and behaviours (Mase, Gramig et al. 2017, Ji and Cobourn 2021, Zappalá 2024). Building on this evidence, we describe a plausible decision-making pathway as "experience-belief-intention-behaviour".

Table 3
Posterior results for the influence of experience on the anticipated rainfall distribution.

Independent variables	Posterior mean estimates	Standard deviation	95% CI/PPI	$\hat{R}$
Subjective loss experience	0.77	0.16	0.48-1.08*	1.00
Gender	0.58	0.37	-0.14-1.29	1.00
Years of living in the study area	0.05	0.10	-0.14-0.24	1.00
Education	-0.06	0.19	-0.43-0.30	1.00
Vineyard location	0.07	0.09	-0.11-0.24	1.00
Ease of hiring workers	-0.69	0.36	-1.37--0.01*	1.00
Off-farm income	0.14	0.13	-0.10-0.39	1.00

Note: This model is estimated using the Bayesian ordered logit model. * indicates that 95% credible interval does not include zero. The $\hat{R}$ of the variance parameters are estimated by Pystan.

In addition, the 95% CI for "Ease of hiring workers" is from -1.37 to -0.01, and the average posterior is -0.69. The credible interval does not include zero. So, these results suggest that the availability of hired labour is significantly associated with farmers' subjective expectations regarding the potential losses from future rainfall shocks, with the relationship being negative. This implies that farmers who perceive hired labour to be more readily available tend to anticipate lower losses in the event of future rainfall. A possible explanation is that abundant labour supply reduces farmers' vulnerability to extreme weather shocks. Compared with farmers facing labour shortages, those who can easily access hired workers are better able to mobilize labour for emergence responses, such as applying pesticides or removing damaged fruit when unexpected rainfall occurs, thereby mitigating potential production losses. In this context, farmers may link their stronger capacity for risk buffering and coping to their perceptions of future climate risks, leading them to form more optimistic expectations about the frequency or severity of future rainfall. This finding may provide support for the hypothesis that risk perception is shaped not only by objective environmental conditions but also by the resources and coping strategies available to individuals (Grothmann and Patt 2005, Van Valkengoed and Steg 2019).

4.4. The impacts of experiences on risk preferences

In the above section, we conclude that farmers show different risk curvatures and probability distortions in gains and losses. Here we verify that, firstly, individual risk preferences could be influenced by personal experience, and that preferences are not as stable as classical economics assumes; and secondly, the effects of experience utility on risk preferences are distinct between the gain and loss domains.

Seven separate Bayesian linear models are applied for seven risk preference parameters (Table 4). We pay particular attention to explaining the impact of experience on the risk preferences and omit explaining the effects of control variables. The detailed results of the regressions are showed in Appendix B, Tables B3 through B9. Results presented in Table 4 allow us to explore our research question two: do personal experiences alter individual risk preferences, and do the effects differ when people face benefits and losses. The 95% CI for risk aversion in the loss domain is between 0.05 and 0.11, which does not contain the null effect (that is, zero). Loss experience of grape production therefore appears to significantly change the degree of farmers' risk aversion in the loss domain. The positive value of the posterior estimate (0.08) implies that farmers who suffered more damages from the rain last year tend to be more risk averse when facing negative future scenarios. Compared with the results in the loss domain, people's loss experience does not appear to influence their risk aversion in the gain domain. In addition, according to the 95% CI of loss aversion, we can be 95% confident that the actual effect would lie between 0.06 and 0.15. This result suggests that farmers' past loss experience significantly increase their aversion to potential future losses.

Section 4.2 found that farmers exhibit different cognitive biases regarding the probabilities of gains and losses. Correspondingly, experience differentially impacts their cognitive biases across various domains. For the gain prospects, the confidence interval for the regression coefficient of experience on the weighting of largest gains is strictly positive, indicating that loss experience affects individuals' beliefs about the probabilities of gains. The positive coefficient suggests more prior rainfall production shocks will result in farmers being less optimistic about the future probabilities of gains. The average estimate of the effect of experience on the degree of sensitivity with respect to changes in gain probabilities is 0.04. The significant positive value suggests that loss experience mitigates the inverse-S shape of the gain-domain probability function, making subjective probabilities more closely aligned with objective probabilities and shifting the weighting function toward a flatter shape. In other words, past losses can reduce farmers' subjective bias of the probability of returns.

Table 4
Posterior results for the influence of experience on farmers risk preferences.

Dependent variables	Posterior mean estimates	Standard deviation	95% CI/PPI	$\hat{R}$
Risk aversion for gains	0.03	0.02	-0.01-0.07	1.00
Risk aversion for losses	0.08	0.02	0.05-0.11*	1.00
Loss aversion	0.11	0.02	0.06-0.15*	1.00
The weighting of the largest gains	0.04	21.73	0.02-0.06*	1.00
Likelihood sensitivity in the gain domain	0.04	20.92	0.02-0.06*	1.00
The weighting of the largest losses	0.05	0.01	0.03-0.07*	1.00
Likelihood sensitivity in the loss domain	0.03	0.02	-0.01-0.06	1.00

Note: All the models are estimated through the Bayesian linear model and include controls for age, gender, income, education, health status. * indicates that 95% credible interval does not include zero. The $\hat{R}$ of the variance parameters are estimated by Pystan.

For the loss prospects, the average effect of experience on the weighting of the largest losses is 0.05, with a 95% CI ranging from 0.03 and 0.07. This suggests that we are 95% confident that the true parameter value lies within this range. Since the confidence interval does not include zero, we can conclude that past losses significantly increase the highest elevation of weighting functions in the losses. Farmers already exhibit an optimistic bias by underweighting the objective probability of unfavourable outcomes, and past loss experiences appear to amplify this bias. One possible explanation is that farmers interpret extreme losses as rare events, and after experiencing such shocks, they may believe that similar extreme outcomes are less likely to occur again. In the context of this study, this tendency is reflected in farmers lowering their perceived probability of experiencing the maximum loss caused by rainfall after undergoing production shocks.

We further conducted an extended analysis to explore the role of risk preference in shaping farmers' climate change adaptation decisions (Appendix B, Tables B10a-B10b). The results show that both risk aversion and loss aversion significantly influence farmers' willingness to adopt adaptation measures. These findings are consistent with previous studies, which emphasise that risk preference is a key determinant of adaptive behaviour (Jin, Xuhong et al. 2020, Visser, Jumare et al. 2020). Taken together with our empirical evidence, this suggests that farmers' past experiences shape their risk preferences, thereby making them more inclined to devote additional effort in future agricultural decisions to avoid potential losses.

5. Extension analysis

5.1 Endogeneity concerns

This study may face potential endogeneity concerns from two main sources. The first is omitted variable bias. Unobservable and difficult-to-control household or individual characteristics may simultaneously influence farmers' evaluations of rainfall-induced profit losses, their expectations about climate risks, and their risk preferences. For instance, mental health conditions may shape risk perceptions (Andreoni, Di Girolamo et al. 2020). Farmers suffering from chronic anxiety or depression may be more likely to overestimate both past losses and future climate risks, thereby exhibiting stronger risk aversion. Similarly, social capital and interpersonal networks may matter (Babcicky and Seebauer 2017, Wang, Zhao et al. 2021). Farmers with extensive mutual-aid networks are better able to obtain assistance during sudden rainfall events, which may reduce their perceived losses and make them more willing to tolerate risk. In practice, it is nearly impossible to capture all such unobservables, nor can they be directly measured in surveys or experiments.

The second concern is reverse causality. As emphasized in our conceptual framework, what shapes farmers' expectations and risk preferences may not be objective experiences, but rather their subjective interpretations of those experiences. In other words, the "experience" in our model reflects *experienced utility*, defined as farmers' beliefs about past events. However, risk preferences themselves may influence how farmers retrospectively evaluate past experiences, giving rise to potential reverse causality. To mitigate both omitted variables and reverse causality, we adopt an instrumental variable (IV) strategy using two-stage least squares (2SLS) (Mogstad, Torgovitsky et al. 2021). Specifically, we follow the previous studies by using soil texture as an instrument for farmers' subjective evaluations of rainfall-related profit losses (Carranza 2014, Afridi, Bishnu et al. 2023). The validity of this instrument requires relevance and exogeneity.

Relevance. Soil texture directly shapes how rainfall affects grape yields and profits. Fieldwork indicates that the study area is dominated by sandy and clay soils. Sandy soils drain well and allow excess rainfall to percolate (Brady, Weil et al. 2008, Osman 2012), thereby reducing the risk of waterlogging and profit losses, leading to lower perceived losses among farmers. By contrast, clay soils drain poorly, making grapes more susceptible to waterlogging and root rot during heavy rainfall (Gutter, Baumgartner et al. 2004), which increases perceived losses. Soil texture is therefore strongly correlated with subjective loss assessments.

Exogeneity. Soil texture is a natural endowment that does not directly influence farmers' personalities or risk preferences. During the initial "Household Responsibility System" reform, land was largely allocated randomly, leaving farmers little opportunity to select plots based on soil quality or personal characteristics (Tan, Heerink et al. 2006). In the subsequent efforts to address farmland fragmentation, the government encourages farmers to lease or contract land in contiguous plots, which may reduce the extent to which farmers can select plots based on soil characteristics (Xin and Li 2019). Thus, soil texture influences risk assessments only through its impact on the consequences of rainfall for grape production, not directly through farmers' beliefs and risk preferences, thereby satisfying the exogeneity condition.

In our field survey, we recorded the soil texture of each farmer's vineyard. Among them, 36.77% of vineyards had sandy soils, 31.61% had clay soils, and the remainder contain a mixture of both soil types. Having established the theoretical validity of the instrument, we next test its empirical strength. According to the two-stage least squares (2SLS) regression results reported in Tables 5a to 5c, the first-stage F-statistics for the models examining the impact of experience on anticipated rainfall distribution and on risk preferences are 22.75 and 57.04, respectively. Both values are well above the conventional threshold of 10, thereby rejecting the null of weak instruments (Du, Zheng et al. 2022, Fu, Ge et al. 2022). Moreover, compared with the Bayesian model estimates presented in Tables 3 and 4, we find that the effect of loss experience on anticipated rainfall distribution and risk preferences remains highly consistent in both direction and significance. Taken together, these results suggest that our main findings remain robust even after accounting for potential endogeneity concerns.

Table 5a

IV regressions: the impact of experiences on anticipated rainfall distribution.

	Experience	Anticipated rainfall distribution
IV	0.27 ***	
	(0.06)	
Experience		0.16*
		(0.09)
Controls	Yes	Yes
1st-stage F		22.75
Observations	155	155

Note: This model is estimated using the 2SLS approach. Control variables consistent with those in the main model, include gender, years of living in the study area, education, vineyard location, ease of hire workers, have ever adopted adaptation methods, and off-farm income. Standard errors clustered at the village level are reported in parentheses. Significance levels: *** $p < 0.01$, * $p < 0.1$.

Table 5b

IV regressions: the impacts of experiences on risk preferences (Gain domain).

	Experience	Risk aversion	Weighting of largest gains	Likelihood sensitivity
IV	0.33 ***			
	(0.04)			
Experience		0.06	0.05***	0.02***
		(0.08)	(0.01)	(0.00)
Controls	Yes	Yes	Yes	Yes
1st-stage F		57.04	57.04	57.04
Observations	155	155	155	155

Note: All the models are estimated using the 2SLS approach. Control variables consistent with those in the main models, include age, gender, total income, off-farm income, education, health status. Standard errors clustered at the village level are reported in parentheses. Significance levels: *** $p < 0.01$.

Table 5c

IV regressions: the impacts of experiences on risk preferences (Loss domain).

	Experience	Risk aversion	Loss aversion	Weighting of largest losses	Likelihood sensitivity
IV	0.33 ***				
	(0.04)				
Experience		0.21**	0.22***	0.15*	0.00
		(0.10)	(0.04)	(0.09)	(0.02)
Controls	Yes	Yes	Yes	Yes	Yes
1st-stage F		57.04	57.04	57.04	57.04
Observations	155	155	155	155	155

Note: All the models are estimated using the 2SLS approach. Control variables consistent with those in the main models, include age, gender, total income, off-farm income, education, health status. Standard errors clustered at the village level are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2 Heterogeneous analysis

In the above analysis, we found that farmers' past experiences influence their adaptive decisions by shaping expectations of future climate risks and personal risk preferences. Building on this finding, we further explore whether such "experience effects" differ across farmers with distinct demographic and socioeconomic characteristics. Specifically, our analysis proceeds in two parts: the first investigates the heterogeneity of experience effects on expectations of future climate risks. The second examines the heterogeneity of experience effects on risk preferences.

In the model analysing the impact of loss experience on expectations of future climate risks, we introduced interaction terms between experience and farmers' demographic characteristics (such as gender, age, income, and land size). The results indicate that only land size plays a significant moderating role. As reported in Column 2 of Appendix B, Table B11a, the impact of loss experience on expectations of future rainfall distribution is significantly stronger among smallholders, but notably weaker among farmers with larger landholdings. This finding can be explained by the fact that large-scale farmers typically operate more diversified production portfolios and have a greater ability to spread risk (Bellon, Kotu et al. 2020, Ahmad, Smale et al. 2023). Consequently, a single loss exerts only a limited effect on their overall income and livelihood stability, reducing their economic and psychological sensitivity to past shocks and, in turn, weakening the role of experience in shaping expectations of future climate risks. By contrast, smallholders tend to be more dependent on a single crop and possess weaker coping capacities (Morton 2007, Clay and King 2019), which makes them perceive losses more acutely and incorporate them more directly into their expectations of future risks.

In the model analysing the impact of loss experience on risk preferences, we similarly incorporated interaction terms between experience and farmers' demographic and socioeconomic characteristics. The results reveal significant heterogeneity with respect to total income and education. As shown in Columns 3-7 of Appendix B, Table B11a, low-income farmers are more strongly influenced by past experiences when forming their risk preferences. A plausible explanation is that these farmers often lack savings and diversified income sources, leaving them with few financial buffers against shocks. As a result, a single adverse event is more likely to be perceived as catastrophic, heightening their sensitivity to future risks. Furthermore, as reported in Appendix B, Table B11b, farmers with lower education levels also display stronger experience effects in shaping their risk preferences. This can be explained in two possible ways. First, lower education restricts farmers' ability to acquire and process external information (Cole and Fernando 2021, Ruzzante, Labarta et al. 2021), making them more reliant on vivid and recent personal experiences when evaluating risks. Second, less-educated farmers are often less able to understand and utilise effective risk management tools such as insurance or advanced agricultural technologies (Reimers and Klasen 2013, Barham, Chavas et al. 2018), which further amplifies the salience of subjective experience in shaping their risk attitudes.

Overall, this section demonstrates that land size, total income, and education are key factors underlying heterogeneity in experience effects. The behavioral consequences of adverse experiences are most pronounced among smallholders, low-income households, and less-educated farmers. This underscores the critical role of individual characteristics in shaping experience effects and suggests that risk management and adaptation policies should pay particular attention to these vulnerable groups.

6. Discussion

The literature seems to have reached a consensus that people who have experienced negative climate or weather events are more inclined to believe and be concerned about global climate change (McDonald, Chai et al. 2015, Osberghaus and Fugger 2022), to support climate policies (Hoffmann, Muttarak et al. 2022), and to show willingness to respond to climate change (Noll, Filatova et al. 2022). However, there is a lack of in-depth exploration of how experiences influence or form future climate change beliefs, intentions and behaviours, as well as the impact processes. This incomplete understanding of how and why individuals adapting to climate change is likely to hinder the promotion and implementation of efficient agricultural adaptation policies.

Our study, contributing to filling this gap in the literature, indicates loss experience related to climate change plays two roles in the decision-making process of farmers' adaptation to climate change, serving both as external prior information in the threat appraisal process; and altering farmers' attitudes and preferences towards future risks and losses. These two aspects jointly contribute to the formation of farmers' subjective outcome distributions of threat events. Previous studies largely ignoring the instability of risk preferences and so the potential influence of climate-related experiences on these preferences are therefore likely to have underestimated the impacts of past experiences in future climate decision-making.

There is plenty of evidence in the literature that agents do not always have perfect information and accurate assessment of weather events (Bhave, Conway et al. 2016), and this is likely to hinder effective adaptation, thereby exacerbating climate impacts (Zappalá 2024). Evidence is similarly found in our study. We asked farmers about their expectations with regard to the number of rainy days in the upcoming harvest season. Their answers suggest Xinjiang grape growers tend to far underestimate the future rainfall frequency (three to four fewer days of rainfall), even though the rain showers during the harvest have greatly affected the grape production. Future research could both provide important detail on the extent to which farmers are misunderstanding climate trends and related consequences, and could also address how to reduce these cognitive biases. Personal experiences of weather and climate-related events can decrease the psychological distance of individuals and climate impacts (McDonald, Chai et al. 2015), and thus it is likely to be cost effective to increase investments in climate loss assessments and consulting services to help farmers form more accurate climate information.

We find that farmers in Xinjiang exhibit different characteristic patterns of risk preferences in the gain and loss domains. To our knowledge, this is the first paper to elicit Chinese farmers' risk preference parameters by adopting Prelec's two-parameter probability functions, which has the advantage of being able to capture individual preferences toward the largest gains and losses. Most existing research on Chinese farmers' risk preferences focuses on risk preferences in the gain domain based on Expected Utility Theory (Tong, Swallow et al. 2019, Gao, Grebitus et al. 2022) or follows the research of Liu & Huang (2013) applying Prospect Theory but assumes the same risk curvatures and probability bias between the gains and losses (Mao, Zhou et al. 2019, Zhou, Aoki et al. 2024). These assumptions are inconsistent with our results, that farmers have different risk preference patterns in different domains.

For our sample of farmers, the profile of the weighting functions displays an inverse-S-shaped in the gain domain, while it is a convex curve below the diagonal in the loss domain. In behavioural terms this suggests that in the positive prospect, farmers on average tend to overweight less likely events (that is, extreme events with low probabilities) and slightly underweight more certain events (that is, events with large probabilities). In the negative prospect, farmers tend to be optimistic and underestimate the probabilities of already suffered losses or anticipated losses. In terms of the shape of weighting functions, our results are different from the research of Tversky and Kahneman (1992) in which the probability weightings are dictated by the inversed-S forms in both gain and loss domains. Our findings support the viewpoint of Wakker (2010, p.228) that "[i]n general, probability weighting is a less stable component than outcome utility". Our findings suggest that researchers therefore should not arbitrarily conclude that weighting functions should always be of the inversed-S types, that is, people will overweight low-probability events and underestimate medium- and high-probability events (Balcombe and Fraser 2015).

Our findings also suggest that Chinese farmers' risk preferences are far from stable, which differs from the assumption in classical economic theory. We elicit farmers' self-reported losses in the previous harvest period, which represent personal *experience utility,* which could be defined by individual instant or retrospective evaluations of experience. We conclude that experience utility could alter farmers' risk preferences. Combined with the conclusion that farmers have different risk preferences between the gain domain and the loss domain, our paper also demonstrates that there are different effects of experience utility on risk preferences towards benefits and losses. Specifically, past production losses do not statistically influence farmers' risk aversion in the gain domain but significantly make farmers more risk averse and loss averse when facing negative scenarios.

Finally, farmers' prior experiences could affect individual biases toward the objective probability of an event. It has been received wisdom in social psychology that "people are often over-optimistic about the future" (Chambers, J. R. et al., 2003, p.1343) and "people tend to think they are invulnerable" (Weinstein, 1980, p.806). Our empirical results support the above.

On average, farmers in our sample exhibit optimism in both gain and loss prospects. However, past loss experiences affect these domains asymmetrically. In the gain domain, they reduce optimism by aligning subjective probabilities more closely with objective ones, while in the loss domain, they amplify optimism by further lowering the perceived likelihood of unfavorable outcomes.

7. Conclusion

This paper focuses on the key antecedents of decision-making emphasised by prospect theory and, based on experimental observations from rural China, uncovers the underlying pathways through which experience shapes decisions. We argue that farmers' adaptation decisions depend not only on expectations of the future but also on their past experiences. Experience not only serves as external information in the decision-making process as assumed by conventional economic theory but, more importantly, it can influence how this external information is used by altering individual risk preferences, thereby shaping behaviour at a deeper level.

This study offers several policy implications for China and other climate-vulnerable regions. On the one hand, strengthening risk-awareness training and providing accessible climate information services (such as mobile alerts and village-level announcements) can help farmers form more accurate expectations about future conditions and reduce their reliance on personal experience alone. On the other hand, when promoting adaptive measures, policymakers should focus on reducing farmers' perceived risks and potential losses, with particular attention to vulnerable groups such as low-income households, small-scale farmers, and those with lower levels of education. For example, in promoting adaptive measures such as rain covers, governments and cooperatives could organise on-site demonstrations and provide transparent cost-benefit information, and supplement these efforts with subsidies or risk-sharing mechanisms. Such initiatives would both improve farmers' understanding of the protective and economic value of adaptation and lower their concerns about downside risks, thereby fostering broader adoption.

Our study has several limitations. First, although the proposed framework of climate adaptation decision-making emphasises the dynamic nature of risk preferences, cross-sectional data cannot capture within-individual changes over time. Future work should employ longitudinal data to verify these dynamics. Second, although we apply Bayesian methods to mitigate small-sample concerns, larger datasets are needed to test the framework more rigorously and further establish its robustness. Third, our empirical analysis is based on grape growers in Xinjiang, China. Xinjiang differs from other regions in its natural and socioeconomic conditions, and viticulture is a specialty crop that may not represent the behaviour of staple-crop farmers, raising concerns about external validity. Nonetheless, the case remains valuable because, like many climate-vulnerable farming communities worldwide, farmers in Xinjiang face high exposure to climate risks, fragile livelihoods, and low adoption of adaptation measures. We therefore emphasise that while our empirical findings are context-specific, the proposed conceptual framework is intended to be broadly generalisable, and future research should test and extend it across other crops, regions, and countries.

Appendix A. Texts

Text A1

Priors and Hyperpriors in models for estimating risk preferences

This research assign that the priors for the individual-level risk preference parameters are normally distributed, spanning a reasonable range to exclude theoretically implausible values and allowing enough space to include parameter values obtained in previous research. The priors for α_i, β_i range from 0 to 2; and from 0 to 5 for λ_i; from 0.5 to 2 for γ_i, δ_i, ξ_i and η_i; and above 0 for θ_i (cf. Kairies-Schwarz et al., 2017; Glockner & Pachur, 2012; Prelec, 1998). Specifically, α_i, β_i, λ_i, γ_i, δ_i, ξ_i, and η_i are characterized by Normal priors:

$$\alpha_i \sim N(\alpha, {\sigma_\alpha}^2); 0 < \alpha_i < 2$$
$$\beta_i \sim N(\beta, {\sigma_\beta}^2); 0 < \beta_i < 2$$
$$\lambda_i \sim N(\lambda, {\sigma_\lambda}^2); 0 < \lambda_i < 5$$
$$\gamma_i \sim N(\gamma, {\sigma_\gamma}^2); 0.5 < \gamma_i < 2$$
$$\delta_i \sim N(\delta, {\sigma_\delta}^2); 0.5 < \delta_i < 2$$
$$\xi_i \sim N(\xi, {\sigma_\xi}^2); 0.5 < \xi_i < 2$$
$$\eta_i \sim N(\eta, {\sigma_\eta}^2); 0.5 < \eta_i < 2$$
$$\theta_i \sim N(\theta, {\sigma_\theta}^2);\ \ \theta_i > 0$$

Diffuse Normal hyperpriors and intervals are applied to the parameters α, β, λ, γ, δ, ξ, η and θ, given by

$$\alpha, \beta \sim N(1, 0.5);\ \ 0 < \alpha < 2;\ 0 < \beta < 2$$

$$\lambda \sim N(1, 0.5);\ \ 0 < \lambda < 5$$

$$\gamma, \delta, \xi, \eta \sim N(1, 0.33);\ \ 0.5 < \gamma < 2;\ \ 0.5 < \delta < 2;\ 0.5 < \xi < 2;\ \ 0.5 < \eta < 2$$

$$\theta \sim N(1, 3);\ \ \theta > 0$$

And there is a diffuse Cauchy hyperpriors for ${\sigma_\alpha}^2$, ${\sigma_\beta}^2$, ${\sigma_\lambda}^2$, ${\sigma_\delta}^2$, ${\sigma_\xi}^2$, ${\sigma_\eta}^2$ given by

$${\sigma_\alpha}^2,\ {\sigma_\beta}^2,\ {\sigma_\lambda}^2,\ {\sigma_\gamma}^2,\ {\sigma_\delta}^2,\ {\sigma_\xi}^2,\ {\sigma_\eta}^2 \sim cauchy(0, 0.33); 0 < {\sigma_\alpha}^2 < 1,\ 0 < {\sigma_\beta}^2 < 1,\ 0 < {\sigma_\lambda}^2 < 1,$$
$$0 < {\sigma_\delta}^2 < 1,\ 0 < {\sigma_\xi}^2 < 1,\ 0 < {\sigma_\eta}^2 < 1$$

$${\sigma_\theta}^2 \sim cauchy(0, 1);\ \ 0 < {\sigma_\lambda}^2 < 5$$

Appendix B. Tables

Table B1

Experimental design for the lucky wheel game

Group one	WheelX1	WheelX2	WheelX3	WheelP1	WheelP2	WheelP3	SureX1	SureP1	TypeW	TypeS	EV_DIFF
1	-9.5	-9.5	0	0.5	0.3	0.2	-7.5	1	negative	negative	-0.1
2	1.5	5	10	0.3	0.1	0.6	6.5	1	positive	positive	0.45
3		-4.5	10	0.3	0.7		2	1	mixed	positive	3.65
4	-10	4.5	6.5	0.1	0.85	0.05	0	1	mixed	zero	3.15
5	-8.5		8.5	0.3		0.7	-1	1	mixed	negative	4.4
6	-7	0	8.5	0.5	0.05	0.45	-1.5	1	mixed	negative	1.825
7	-9.5	-9.5	-2.5	0.15	0.4	0.45	-6	1	negative	negative	-0.35
8	-9.5	-5	-1.5	0.3	0.3	0.4	-4.5	1	negative	negative	-0.45
9		-9	-1.5	0.35	0.65		-4	1	negative	negative	-0.125
10	-1	0	9.5	0.4	0.35	0.25	2	1	mixed	positive	-0.025

Group two	WheelX1	WheelX2	WheelX3	WheelP1	WheelP2	WheelP3	SureX1	SureP1	TypeW	TypeS	EV_DIFF
1	-9.5	-6.5	-0.5	0.6	0.15	0.25	-7	1	negative	negative	0.2
2	-9	3		0.45	0.55		-3	1	mixed	negative	0.6
3	-8	0	8.5	0.1	0.6	0.3	0	1	mixed	zero	1.75
4	-7	0	9	0.05	0.55	0.4	2.5	1	mixed	positive	0.75
5	-5	0	9	0.05	0.4	0.55	3	1	mixed	positive	1.7
6	0.5	9	9.5	0.55	0.05	0.4	4	1	positive	positive	0.525
7	-9	-1	0	0.8	0.15	0.05	-7	1	negative	negative	-0.35
8	-10	-3.5		0.25	0.75		-4.5	1	negative	negative	-0.625
9	-7.5	0.5		0.35	0.65		-1.5	1	mixed	negative	-0.8
10	-9.5	0	9	0.25	0.6	0.15	-1	1	mixed	negative	-0.025

Group three	WheelX1	WheelX2	WheelX3	WheelP1	WheelP2	WheelP3	SureX1	SureP1	TypeW	TypeS	EV_DIFF
1	-9.5	0	6.5	0.5	0.4	0.1	-6	1	mixed	negative	1.9
2	0	2.5	9.5	0.05	0.4	0.55	5.5	1	positive	positive	0.725
3	-10	0	3	0.1	0	0.9	1	1	mixed	positive	0.7
4	-9.5	0	8	0.1	0.75	0.15	0	1	mixed	zero	0.25
5	-8	0	8	0.65	0.3	0.05	-5	1	mixed	negative	0.2
6	-9.5	-1.5		0.75	0.25		-7.5	1	negative	negative	0
7	3	3.5	9	0.4	0.2	0.4	5.5	1	positive	positive	0
8	-9	-2.5	0	0.3	0.45	0.25	-3.5	1	negative	negative	-0.325
9	0	1.5	10	0.1	0.3	0.6	6.5	1	positive	positive	-0.05
10	-8	0		0.75		0.25	-5	1	negative	negative	-1

Group four	WheelX1	WheelX2	WheelX3	WheelP1	WheelP2	WheelP3	SureX1	SureP1	TypeW	TypeS	EV_DIFF
1	-3.5	4.5	9	0.25	0.05	0.7	0	1	mixed	zero	5.65
2	-9.5	0	6.5	0.1	0.6	0.3	0	1	mixed	zero	1
3	-9	0	8.5	0.05	0.8	0.15	0	1	mixed	zero	0.825
4	-0.5		7.5	0.45		0.55	1.5	1	mixed	positive	2.4
5	-7.5	0	9	0.05	0.35	0.6	4.5	1	mixed	positive	0.525
6	-10	-3.5		0.65	0.35		-7.5	1	negative	negative	-0.225
7	-10	0		0.65	0.35		-6.5	1	negative	negative	0
8	-9.5	0	7.5	0.5	0.45	0.05	-4	1	mixed	negative	-0.375
9	-10	-2.5	0	0.2	0.75	0.05	-3.5	1	negative	negative	-0.375
10	-10	0		0.15	0.85		-1.5	1	negative	negative	0

Note: This table illustrates the design of “Lucky Wheel” game. WheelX1, WheelX2 and WheelX3 represent the three possible payoffs from spinning the lucky wheel, while WheelP1, WheelP2 and WheelP3 indicate the corresponding probabilities of these payoffs. SureX1 is the payoff from the money bag. SureP1 is 1, indicating that the return from the money bag is risk-free. TypeW and TypeS refer to the types of payoffs. EV_DIFF denotes the difference in expected value between the lucky wheel and the money bag. Our design aims to ensure that in around 50% of cases, the expected value of the lucky wheel exceeds that of the money bag.

Table B2

Descriptive statistics of samples

Variables	Percent (%)
1. Age distribution:	
Age <=18;	0.0
18< Age <=30;	12.3
30< Age <=40;	20.7
40< Age <=50;	48.4
50< Age <=60;	14.2
Age >60.	4.5
2. Gender distribution:	
Female	47.7
Male	52.3
3. Education level:	
0 years	3.2
1-6 years	23.9
7-9 years	45.8
10-12 years	21.3
Education >12 years	5.8

4. Health status:	
Very good	34.2
Good	32.9
Fair	31.6
Poor	1.3
Very poor	0.0
5. Total income:	
Income <= 10000;	5.81
10000< Income<= 30000;	25.16
30000< Income <= 50000;	26.45
50000< Income <=70000;	25.81
70000< Income <= 100000;	10.32
Income > 100000;	6.45
6. Off-farm income:	
Income <= 2000;	54.8
2000< Income<= 5000;	20.0
5000< Income <= 10000;	11.0
10000< Income <=15000;	4.5
15000< Income <= 20000;	5.8
Income > 200000.	3.9
7. Planting years of grapes:	
Years <= 3;	1.9
3 <Years <= 5;	12.9
5 < Years <= 10;	29.7
10 < Years <= 15;	31.6
15 < Years <=20;	16.8
Years > 20.	7.1
8. Units of labour in the household:	
Labor forces = 1;	4.5
Labor forces = 2;	77.4
Labor forces = 3;	11.6
Labor forces > = 4;	6.5
9. Sample size:	155

Note: To maximize the protection of the participating farmers' privacy, the questionnaire options are processed in segments.

Table B3

Posterior results for the influence of experience on risk aversion for gains

Independent variables	Posterior mean estimates	Standard deviation	95% CI/PPI	$\hat{R}$
Subjective loss experience	0.03	0.02	-0.01-0.07	1.00
Age	0.12	0.02	0.08-0.16*	1.00
Gender	0.05	0.05	-0.05-0.15	1.00
Total income	0.05	0.02	0.01-0.09*	1.00
Off-farm income	-0.01	0.02	-0.05-0.02	1.00
Education	0.11	0.02	0.06-0.15*	1.00
Health status	-0.002	0.03	-0.06-0.06	1.00

Note: This model is estimated using the Bayesian linear model. * indicates that 95% credible interval does not include zero. The $\hat{R}$ of the variance parameters are estimated by Pystan.

Table B4

Posterior results for the influence of experience on risk aversion for losses

Independent variables	Posterior mean estimates	Standard deviation	95% CI/PPI	$\hat{R}$
Subjective loss experience	0.08	0.02	0.05-0.11*	1.00
Age	0.08	0.02	0.05-0.11*	1.00
Gender	0.09	0.04	0.01-0.16*	1.00
Total income	0.04	0.02	0.01-0.07*	1.00
Off-farm income	0.03	0.01	0.01-0.06*	1.00
Education	0.06	0.02	0.02-0.10*	1.00
Health status	0.04	0.02	-0.01-0.09	1.00

Note: This model is estimated using the Bayesian linear model. * indicates that 95% credible interval does not include zero. The $\hat{R}$ of the variance parameters are estimated by Pystan.

Table B5

Posterior results for the influence of experience on loss aversion

Independent variables	Posterior mean estimates	Standard deviation	95% CI/PPI	$\hat{R}$
Subjective loss experience	0.11	0.02	0.06-0.15*	1.00
Age	0.19	0.02	0.16-0.24*	1.00
Gender	0.17	0.06	0.06-0.27*	1.00
Total income	0.07	0.02	0.03-0.11*	1.00
Off-farm income	0.03	0.02	-0.01-0.07	1.00
Education	0.18	0.03	0.13-0.23*	1.00
Health status	0.07	0.03	0.01-0.14*	1.00

Note: This model is estimated using the Bayesian linear model. * indicates that 95% credible interval does not include zero. The $\hat{R}$ of the variance parameters are estimated by Pystan.

Table B6

Posterior results for the influence of experience on the weighting of the largest gains

Independent variables	Posterior mean estimates	Standard deviation	95% CI/PPI	$\hat{R}$
Subjective loss experience	0.04	0.01	0.02-0.06*	1.00
Age	0.09	0.01	0.08-0.11*	1.00
Gender	0.08	0.02	0.04-0.13*	1.00
Total income	0.03	0.01	0.01-0.05*	1.00
Off-farm income	0.01	0.01	-0.002-0.03	1.00
Education	0.09	0.01	0.07-0.11*	1.00
Health status	0.04	0.01	0.02-0.07*	1.00

Note: This model is estimated using the Bayesian linear model. * indicates that 95% credible interval does not include zero. The $\hat{R}$ of the variance parameters are estimated by Pystan.

Table B7

Posterior results for the influence of experience on likelihood sensitivity in the gain domain

Independent variables	Posterior mean estimates	Standard deviation	95% CI/PPI	$\hat{R}$
Subjective loss experience	0.04	0.01	0.02-0.06*	1.00
Age	0.10	0.01	0.08-0.11*	1.00
Gender	0.08	0.02	0.04-0.13*	1.00
Total income	0.03	0.01	0.02-0.05*	1.00
Off-farm income	0.01	0.01	-0.01-0.03	1.00
Education	0.09	0.01	0.07-0.12*	1.00
Health status	0.04	0.01	0.01-0.07*	1.00

Note: This model is estimated using the Bayesian linear model. * indicates that 95% credible interval does not include zero. The $\hat{R}$ of the variance parameters are estimated by Pystan.

Table B8

Posterior results for the influence of experience on the weighting of the largest losses

Independent variables	Posterior mean estimates	Standard deviation	95% CI/PPI	$\hat{R}$
Subjective loss experience	0.05	0.01	0.03-0.07*	1.00
Age	0.11	0.01	0.09-0.13*	1.00
Gender	0.09	0.03	0.04-0.15*	1.00
Total income	0.03	0.01	0.01-0.05*	1.00
Off-farm income	0.02	0.01	0.001-0.04*	1.00
Education	0.11	0.01	0.09-0.13*	1.00
Health status	0.05	0.02	0.02-0.09*	1.00

Note: This model is estimated using the Bayesian linear model. * indicates that 95% credible interval does not include zero. The $\hat{R}$ of the variance parameters are estimated by Pystan.

Table B9

Posterior results for the influence of experience on likelihood sensitivity in the loss domain

Independent variables	Posterior mean estimates	Standard deviation	95% CI/PPI	$\hat{R}$
Subjective loss experience	0.03	0.02	-0.01-0.06	1.00

Age	0.15	0.02	0.11-0.19*	1.00
Gender	0.10	0.05	0.01-0.19*	1.00
Total income	0.04	0.02	0.01-0.08*	1.00
Off-farm income	-0.01	0.02	-0.04-0.03	1.00
Education	0.14	0.02	0.10-0.19*	1.00
Health status	0.02	0.03	-0.04-0.07	1.00

Note: This model is estimated using the Bayesian linear model. * indicates that 95% credible interval does not include zero. The $\hat{R}$ of the variance parameters are estimated by Pystan.

Table B10a

Risk aversion (losses) and willingness to purchase rain covers in the next five years.

	Ordered logit model		Ordered logit model		Bayesian ordered logit model	
Independent variables	Mean estimates	P value	Mean estimates	P value	Posterior mean estimates	95% CI/PPI
Risk aversion	1.57	0.02	1.91	0.01	1.94	0.57-3.32
Gender	-	-	-0.65	0.03	-0.68	-1.30--0.05
Years in study area	-	-	-0.14	0.10	-0.14	-0.31-0.02
Education	-	-	0.20	0.24	0.20	-0.14-0.55
Vineyard location	-	-	-0.09	0.26	-0.09	-0.24-0.06
Ease of hiring workers	-	-	-0.20	0.52	-0.21	-0.82-0.41
Off-farm income	-	-	0.22	0.07	0.23	-0.01-0.47

Note: The first two models are estimated using the frequentist approach, while the third is estimated using the Bayesian approach.

Table B10b

Loss aversion and willingness to purchase rain covers in the next five years.

	Ordered logit model		Ordered logit model		Bayesian ordered logit model	
Independent variables	Mean estimates	P value	Mean estimates	P value	Posterior mean estimates	95% CI/PPI
Loss aversion	2.12	0.04	2.15	0.04	2.14	0.08-4.26

Gender	-	-	-0.56	0.07	-0.57	-1.18-0.03
Years in study area	-	-	-0.10	0.24	-0.10	-0.28-0.07
Education	-	-	0.15	0.39	0.15	-0.18-0.49
Vineyard location	-	-	-0.08	0.32	-0.08	-0.23-0.07
Ease of hiring workers	-	-	-0.14	0.64	-0.15	-0.76-0.46
Off-farm income	-	-	0.25	0.04	0.26	0.03-0.50

Note: The first two models are estimated using the frequentist approach, while the third is estimated using the Bayesian approach.

Table B11a
Heterogeneous analysis.

	Anticipated rainfall distribution	Risk aversion for losses	Loss aversion	Weighting of largest gains	Likelihood sensitivity for gains	Weighting of largest losses
Experience	2.11 [1.04-3.19]*	0.15 [0.09-0.21]*	0.41 [0.34-0.48]*	0.19 [0.16-0.22]*	0.20 [0.17-0.23]*	0.30 [0.24-0.36]*
Landsize	1.9 [-0.36-4.17]					
Experience × Landsize	-1.18 [-2.10--0.28]*					
Total income		0.31 [0.21-0.42]*	0.88 [0.75-1.00]*	0.42 [0.37-0.47]*	0.44 [0.38-0.49]*	0.69 [0.57-0.81]*
Experience × Total income		-0.07 [-0.11--0.02]*	-0.26 [-0.31--0.21]*	-0.13 [-0.15--0.11]*	-0.14 [-0.16--0.12]*	-0.23 [-0.28--0.19]*
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: All the models are estimated using a Bayesian approach. Posterior inference was based on 10000 draws after discarding the first 15000 iterations as burn-in. The $\hat{R}$ convergence statistic in all models are below than 1.1. * indicates that 95% credible interval does not include zero. Control variables consistent with those in the main models.

Table B11b
Heterogeneous analysis (continued).

	Risk aversion for losses	Loss aversion	Weighting of largest gains	Likelihood sensitivity for gains	Weighting of largest losses

Experience	0.20 [0.15-0.26]*	0.37 [0.31-0.43]*	0.15 [0.12-0.17]*	0.16 [0.13-0.18]*	0.20 [0.24-0.36]*
Education	0.24 [0.17-0.31]*	0.58 [0.5-0.67]*	0.26 [0.22-0.29]*	0.27 [0.24-0.31]*	0.41 [0.33-0.49]*
Experience × Education	-0.08 [-0.10--0.05]*	-0.17 [-0.2--0.13]*	-0.07 [-0.08--0.05]*	-0.07 [-0.09--0.06]*	-0.11 [-0.15--0.08]
Controls	Yes	Yes	Yes	Yes	Yes

Note: All the models are estimated using a Bayesian approach. Posterior inference was based on 10000 draws after discarding the first 15000 iterations as burn-in. The $\hat{R}$ convergence statistic in all models are below than 1.1. * indicates that 95% credible interval does not include zero. Control variables consistent with those in the main models.

Table B12

Robustness checks for the estimated posterior risk parameter results.

Parameter	Full samples	Subsamples by Excluding Group 2
Risk aversion for gains	0.89	0.88
Risk aversion for losses	0.91	0.86
Loss aversion	1.83	1.74
The weighting of the largest gains	0.87	0.88
Likelihood sensitivity in the gain domain	0.88	0.96
The weighting of the largest losses	1.12	1.13
Likelihood sensitivity in the loss domain	1.03	1.08

Note: This table is to test the influence of the unbalanced design of Group two. The full-sample model was estimated using 8000 draws after discarding the first 24000 draws as burn-in. The subsample model, excluding Group 2, was estimated using 16000 draws after discarding the first 16000 draws as burn-in.

Appendix C. Figures

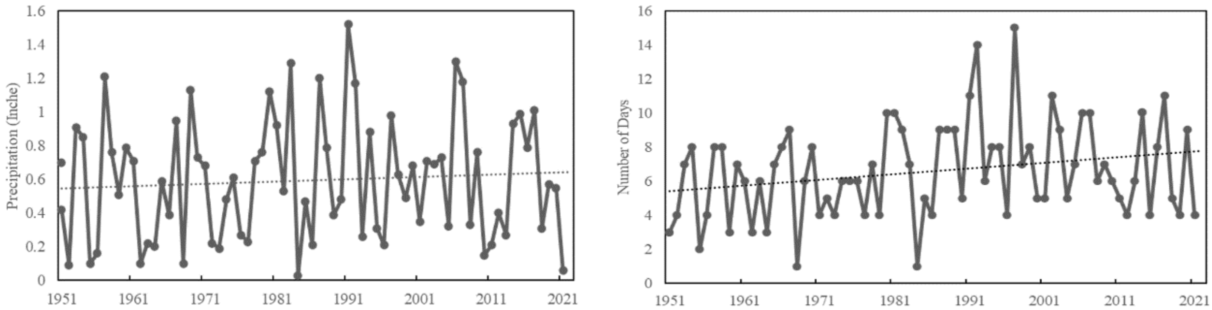

Fig. C1. Precipitation and number of rainy days in Liushuquan, July-September, 1951-2021

Note: The data was collected by the authors from the National Oceanic and Atmospheric Administration (NOAA) and National Meteorological Information Center.

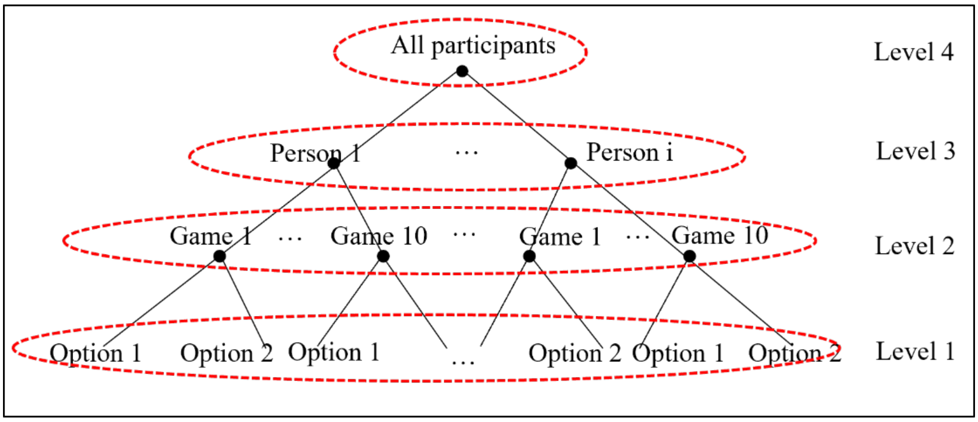

Fig. C2. Mixed Logit tree structure in the experiment

Note: This structure illustrates the different levels of sampling. A total of 155 participants engaged in the experiment, each playing 10 games with two options per game.This results in $155 * 10 = 1550$ observations. The tree structure also clarifies why the research adopts a Bayesian mixed logit model rather than a multinomial logit to estimate farmers' risk preferences. The Bayesian mixed logit model accommodates individual differences and captures preference heterogeneity effectively.

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