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ARTICLE

Experiential Learning, Narrative-Based Learning, and Insurance Adoption: Experimental Evidence from Kenya

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Abstract

We compare the impact of two extension modalities on knowledge accumulation and willingness to pay for a weather index insurance product among smallholder farmers in Kenya. One approach to extension is based on experiential learning and involves participation in an incentivized framed experiment (or game). The other is based on conventional "narrative-based" learning. While both modalities increase farmer knowledge, incentivized gamification causes more learning. We also find that experiential learning affects follow-up demand for the insurance product, which is not true for narrative-based learning. Interestingly, demand for insurance shifts *inward* after playing the insurance game. This reduction in demand is mainly caused by increased knowledge about the insurance product, but we also present suggestive evidence that experiencing basis risk during the game was more salient than theory-based learning about basis risk. Game-based learning is an effective approach to promote knowledge accumulation and may accentuate or attenuate adoption of innovations by updating *ex-ante*, possibly biased, expectations.

KEYWORDS

extension, game-based, incentive compatibility, information, insurance, learning

JEL CLASSIFICATION

O33, O12, Q12, Q14, Q16

1 | INTRODUCTION

A large gap exists between potential and actual crop yields in African smallholder farming. This partly explains why the region trails behind the rest of the world in terms of addressing hunger, malnutrition, and poverty (Tittonell and Giller 2013). It is commonly believed that information transfers that promote the adoption of new technologies by smallholders are important in narrowing the yield gap (Aker, 2011). This includes information about modern technologies (e.g., Foster and Rosenzweig 2010; Macours 2019; Shiferaw et al. 2015; Takahashi et al. 2020)[1] and about how to manage production risk—particularly weather shocks (Burke and Emerick 2016; Karlan et al. 2014). One approach for farmers to mitigate drought risks is adopting index-based weather insurance, but adoption rates of insurance products remain low across target populations (Cole et al. 2013; Platteau et al. 2017; Cole and Xiong 2017). This may reflect the complexity of the insurance product (Ahmed et al. 2020; Platteau et al. 2017). One may expect that addressing informational constraints would increase demand for index insurance. Farmers mostly receive information about new technologies, including insurance products, through agricultural extension services (Anderson and Feder 2004, 2007; Cook et al. 2021). However, current approaches to extension are relatively ineffective (Niu and Ragasa 2018; Norton and Alwang 2020; Bridle et al. 2020; Harou et al. 2022). Since other information transfer modalities, such as social learning, are unable to close the information gap (Suri and Udry 2022), there is a call for innovative approaches to provide extension to smallholders (Kaiser and Menkhoff 2022).

In this paper we evaluate the effectiveness of an alternative extension approach, based on participation in an incentivized game that induces "experiential learning." The game focuses on risk and insurance and is played by a sample of Kenyan farmers. We evaluate how game-based learning affects knowledge about insurance as well as follow-up demand for a real-life index insurance product. Importantly, we compare the performance of experiential learning to the performance of a conventional (narrative-based) extension modality typically used by extension officers (Waddington et al. 2014).

Game-based learning entails the use of games for educational purposes (Dernat et al. 2023; Krath et al. 2021). Several theories on game-based learning and gamification are relevant in light of our study (see Krath et al. 2021), among them is the so-called "experiential learning theory" (ELT; Kolb 2015).[2] ELT provides a holistic perspective to learning and emphasizes the role of direct experience on learning, unlike cognitive learning theories that emphasize acquisition and recall of abstract symbols. Experiential learning theory is built around the concept of reflection: The subject experiences something (through doing), after which she reflects on these experiences and relates them to real-life situations. The learner then forms generalizations (abstract concepts), which are applied to real-life settings.

The education literature shows that game-based learning improves student learning outcomes (Bai et al. 2020). Games are effective because they illustrate goals and goal relevance, nudge users through guided paths, give users immediate feedback, reinforce good performance, and simplify content to manageable tasks (Landers et al. 2018; Plass et al. 2015). Games can mimic realities and induce reflection on experiences during the game—hence the label "experiential learning." Another

[1]The literature on the effects of information transmission on adoption is still inconclusive. Some studies highlight the importance of trainings and extension (see Takahashi et al. (2020) for a review), but others find limited effects, especially when it comes to actual technology adoption and impacts (Harou et al. 2022; Leight et al. 2022; McKenzie 2021). Kaiser and Menkhoff (2022) argue that one way to increase the efficacy of extension is finding alternatives to the conventional descriptive (lecture-based) information delivery. For instance, some studies focused on farmer-to-farmer technology extension, as more efficient extension strategies than traditional public-sector extension approaches (e.g., Nakano et al. 2018). Others consider the role of incentives in favoring dissemination of information through social learning (e.g., Benyishay & Mobarak 2019).

[2]An alternative theory is self-determination theory (SDT), which is a theory of human motivation focusing on three needs: autonomy, competence, and relatedness (Deci & Ryan 2008). Autonomy relates to volition, for example, people engaging in a game out of their own choice. Competence relates to the desire to learn new skills and explore or understand the environment, while relatedness is about people's desire for social relations—which is especially relevant in multiplayer games. Important elements are therefore motivation and engagement.

advantage is that phenomena that usually can only be observed and experienced over a long period of time can be experienced within a relatively short time frame in a game. This is particularly important in agriculture where learning about new technologies, such as index insurance, tends to be complex and slow, because of the delay between decisions and outcomes and because performance depends on the interaction with other factors such as weather realizations (Bold et al., 2017). Finally, playing games can be "fun" so that game-based learning may trigger intrinsic motivation and enable individuals to concentrate for longer, especially when dealing with topics that otherwise are less attractive (Plass et al. 2015).

A growing literature explores the potential role of game-based learning in helping farmers to learn about agricultural innovations (Elabed and Carter, 2015; Klerkx, 2021; Serfilippi and Ramnath 2018). For example, Tjernström et al. (2021) examine how Kenyan farmers respond to an interactive app featuring a virtual farm that is calibrated to resemble their own farm. Participating farmers learn about the returns to different inputs. This is reflected in how they adjust real-life technology choices after the game. We are aware of three papers that study how experiential learning affects demand for crop insurance. These papers document that playing games has the potential to affect demand—shifting either knowledge, preferences, or beliefs of farmers. Cai and Song (2017) play indemnity-based insurance games with rice farmers in China and find that experiences acquired in the game increase take-up. Jensen et al. (2018) use observational data to estimate basis risk of an index-based livestock insurance product in Kenya and examine how playing an insurance game interacted with actual basis risk increases knowledge and demand for insurance. Finally, Janzen et al. (2021) show that game-based learning improves knowledge and increases demand for index insurance among smallholders in Kenya.[3]

We contribute to the literature as follows. Our focus differs from Cai and Song (2017) because we consider basis risk—the possible mismatch between farm-level losses and those measured by the index—as a determinant of insurance adoption. Cai and Song (2017) consider indemnity-based insurance where basis risk does not exist. We randomly vary exposure to basis risk in our game, setting the paper apart from Jensen et al. (2018) who use observational data to study how realized basis risk affects purchase of index-based livestock insurance.[4] Our paper is closest to Janzen et al. (2021), who provide a basic (narrative-based) training to *all* participating farmers and then invite a random subsample of these subjects to also engage in experiential learning. Instead, we randomly assign our subjects to either a conventional narrative-based extension session *or* a game-based learning experience (or a control group), enabling us to isolate the game effect. We also use a binding auction to measure demand in an incentive-compatible fashion and do not rely on stated preferences. Finally, we use mediation analysis to probe the pathways through which the game influences outcomes.

We obtained three main results. First, while both game-based learning and narrative-style learning increase farmers' knowledge about index insurance, we found that game-based learning significantly outperforms the conventional narrative-based approach by around 0.15 Standard Deviations (SD). The finding that experiential learning fosters greater knowledge accumulation is consistent with Cai and Song (2017), Janzen et al. (2021), and others, but is in contrast with other studies (e.g., Gaurav et al. 2011; Tessema et al. 2021). Compared to these latter studies, differences may arise because we used a game where subjects could earn money, depending on their choices in the game. Second, game-based learning shifts demand for the insurance product, but narrative-style learning does not. Perhaps surprisingly to readers who believe that "lack of knowledge" is an impediment to adoption, we found that the impact of experiential learning on adoption is negative, shifting demand inward. Third, the mechanism explaining the reduction in demand is twofold. Game-based learning fosters an improved understanding of the insurance product, which seems to underperform relative to *ex ante* expectations. This does not explain the full effect. Game-based learning also increases the

[3]Other applications include teaching farmers about natural resource management (for example, Assefa et al. 2021), teaching farmers on the trade-offs and synergies in livestock production systems (Dernat et al. 2023), ground-water management (Meinzen-Dick et al. 2018), and agroforestry management (Sari et al. 2024).

[4]Janzen et al. (2021) discuss how this may introduce endogeneity challenges.

salience of basis risk, and subjects exposed to "high basis risk scenarios" in the experiment lose their appetite for index insurance. In other words, the game corrects an overly optimistic image of insurance and creates more realistic expectations, and it also enables farmers to experience the adverse effects of basis risk. Games designed to engender more informed choices about innovations may therefore discourage adoption. This underscores the need to address basis risk in index insurance products.

The remainder of this paper is organized as follows. In the next section, we describe the context, experiment design, and data. Section 3 presents the empirical estimation strategy. Section 4 summarizes the empirical results. Section 5 concludes.

2 | CONTEXT, EXPERIMENT DESIGN, AND DATA

2.1 | Context

Agriculture in Kenya is largely rainfed, and performance varies with weather outcomes. During the period 1980–2010, Kenya experienced 13 droughts, resulting in average annual losses of US$155 million (D'alessandro et al. 2015). Exposure to climate risks varies from county to county. We conducted our study in Meru County, one of the semiarid counties in the Mt. Kenya region. Meru County has seen a decline in economic growth in recent years, following the export ban of *miraa* (Khat)–a major cash crop produced locally (Carrier & Klantschnig 2018). Farmers have switched to other crops, such as maize. Crop insurance could cushion farmers from some of the risks they suffer, especially droughts (Muriithi et al. 2022), but uptake of unsubsidized crop insurance products is low (Bulte et al. 2019).

According to discussions with farmers in the county, uptake is low due to various reasons including unclear terms of insurance policies, negative experiences with existing insurance products (including basis risk), opaque loss verification procedures, and long delays in processing claims. Poor understanding of how insurance works is a major barrier to adoption (Muriithi et al. 2022), and many farmers view crop insurance as an investment that should deliver a return (payout) at the end of the season. Enhancing farmers' understanding of crop insurance as a risk management strategy may increase relevance and shift demand for insurance products (Shin et al. 2022).

2.2 | Sample Selection, Experimental Design, and the Experiential Learning Intervention

Our pool of farmers consists of 1409 farmers who earlier engaged in a household survey for the Innovation for Africa Climate Risk Insurance project conducted in late 2021 and early 2022. In the first sampling stage, we randomly sampled 84 sublocations proportionate to the number of farmers from each of the nine subcounties ("wards") of Meru County. The selection aimed to capture variation in maize production systems across wards. We randomly assigned individual farmers to treatment arms. Half of them were assigned to the game treatment ($n_1 = 700$) and the other half to the narrative treatment ($n_2 = 350$) or control group ($n_3 = 350$) (see experimental design in Figure 1). We block on sublocations, the smallest administrative unit in Kenya, $N = 84$, assigning farmers from each block to the three experimental arms in equal proportions to promote balance.[5] Farmers assigned to the game treatment were subsequently randomly assigned to one of three basis risk levels during the game they played: 5%, 10%, and 15%.

[5]From our power calculations, we needed about 100 "blocks" with an "intercluster correlation" of 0.1, each block with 16 farmers to attain an effect size of 0.25. Using the same assumptions, the 84 blocks gave us a power of 0.8.

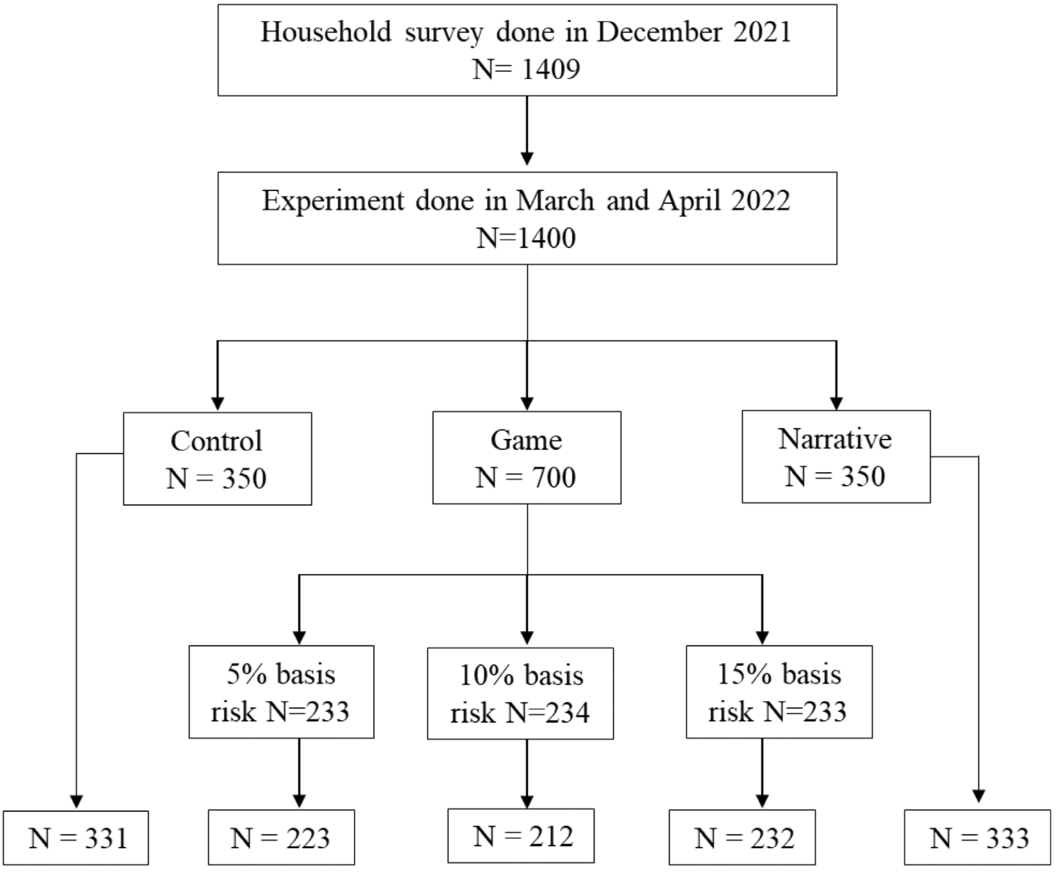

FIGURE 1 Experimental design. The figures at the bottom are the number of farmers who participated in the experiment in each group, in total 1331 farmers.

Farmers in the control group did not receive any information from us about crop insurance. We only mentioned crop insurance during the survey used to assess farmer knowledge about insurance. Farmers in the control group were informed that we wanted to measure their understanding of how index insurance works. After a few warm-up questions, including an optimism bias exercise, we asked them 15 knowledge questions to test their understanding of crop insurance (see below). After this exercise, farmers were given an opportunity to ask questions about index insurance.

Next, we turn to our treatment arms. Interventions were implemented at the farmers' homes between March and April 2022.[6] Farmers were informed one week before the day of the experiment. Enumerators were randomly assigned farmers and received strict instructions to stick to the script. When an enumerator arrived at the farmer's home, he/she introduced him/herself and explained the purpose of the visit. Importantly, participants assigned to the *Game* and the *Narrative* treatments received identical information about index insurance: the content of the narrative was "worked into" the game instructions.

Farmers assigned to the Narrative arm were informed that the training would take 30 minutes, that the aim of the exercise was to learn about how index insurance works, and that they could drop out at any point of the exercise without any repercussions. After participating in the incentivized

[6]This coincided with the main planting season in the region. However, because of logistical challenges, we did not offer the farmers the insurance product then but rather promised to offer the product in the coming cropping season.

game to measure optimism bias, farmers were taught about index insurance. They received the same information as those who played the game. The only difference is that information for the game group was crafted into learning activities that fostered "experience," while the information for the narrative group was delivered through the conventional "lecturing" way. The execution of the game took longer than the narrative session (90 minutes vs. 30 minutes), which potentially is a confounding factor.[7] The information provided to the narrative group included details on crop insurance, types of insurance and types of risks covered by insurance products, insurance premiums, payout conditions, and the concept of basis risk. Details on the information that was provided to the farmers can be found in the Appendix S1 (Table A2).

For farmers assigned to the Game arm, the enumerator explained that the game involved maize production on a hypothetical farm (incurring production costs, experiencing some risks, and getting a harvest at the end of the season) and index insurance. Enumerators informed farmers that the objective of the game was to help them understand how index insurance works, that the whole exercise would take not more than 90 minutes, and that the game provided an opportunity to earn some money (it was incentive compatible). Before the game started, farmers played an incentivized game to gauge optimism bias. Then the enumerator read the game instructions to the farmer and explained each of the instructions until the farmer fully understood them. We asked specific follow-up questions to test whether farmers understood every step of the game.

In the game, farmers produced maize on a hypothetical farm: a one-acre piece of land. The farmer incurred production costs, experienced production risks, had the option to purchase insurance to cushion herself from these risks, and earned revenues from production. We considered two risks that were most frequently cited during the household survey: unreliable rainfall (drought) and pests or diseases. Next, farmers were endowed with 12,000 game shillings to cover production costs, where 100 game shillings were equivalent to 1 Kenyan shilling at the time of payout. Each bag of maize could be sold for 2000 game shillings. After playing a practice round, farmers played three "real" rounds. Round 1 was a repeat of the practice round, involving production without insurance. Round 2 introduced farmers with the opportunity to purchase crop insurance to mitigate production risk. Round 3 introduced basis risk for the insurance product (which we exogenously varied across farmers; see below). Afterwards, one of the rounds was randomly selected for actual payout. We now turn to the details of the game rounds.

Round 1: Yield Realizations

The average yield in the game was 12 bags of maize, roughly the median yield in the study area. Yields varied depending on random drought and pest conditions. To determine how yields were affected by droughts, we offered farmers a jar (Jar A) with 11 beads. Each bead had one of the following numbers written on it: -4, -2, -1, -1, 0, 0, 0, $+1$, $+1$, $+2$, and $+4$.[8] These numbers represent *deviations* from the average yield. The farmer was asked to pick a bead from the jar. We repeated this procedure to determine yield deviations due to pests. We offered the farmer a second jar (Jar B) containing 11 beads with the same numbers. The farmer picked a bead from this jar as well. His or her yield in this round is simply the average yield (12 bags) plus the sum of the two beads. For example, if a farmer picked bead number -2 from Jar A and number -4 from Jar B, her realized yield would be $12 - 4 - 2 = 6$ bags. Under the most favorable production conditions (no drought and no pests) farmers obtained a maximum yield of 20 bags of maize ($12 + 4 + 4$). In the worst-case scenario, they obtained only four bags of maize ($12 - 4 - 4$). These values are in line with evidence from discussions with farmers about harvests locally perceived as very good or very

[7]Farmers were always free to "drop out" of the game if they got tired or bored. This never happened, so we assume that prolonged duration of the game was offset by its "fun" aspect. Farmers remained focused and interested during the game.
[8]We select these numbers to achieve a near normal distribution of yield realizations.

poor. The resulting distribution of yields approximately followed a normal distribution, as shown in Figure A1. The cost of production on this piece of land was game shillings 10,000.[9] Deducting these production costs from the endowment resulted in a bonus of 2000 shillings (12,000–10,000) which we introduced to minimize the "house money effect" in subsequent rounds.

Round 2: Yield Realizations with Crop Insurance

In Round 2 farmers had the option to purchase crop insurance to mitigate production risk. In the game yields vary with drought and pest realizations. Participants were randomly assigned to one of two actuarially identical insurance products, namely "single peril" (covering drought shocks only) or "multiple peril" (covering both shocks). The insurance product mimicked a hybrid insurance product where farmers receive a payout if their realized yield was below the region's average of 12 bags. For each bag below the average, if this was caused by drought, farmers in the "single peril" insurance received KSh. 500. Those in the "multiple peril" insurance received KSh. 500 only if the negative deviations from the average were major (either four bags because of drought, or four bags from pests or diseases, or both), regardless of their cause (drought or pest).[10] This variation ensured that both products were actuarially identical. The main difference between the two is that in one case the insurance covered all types of negative shocks, whilst in the other it only covered one type of shocks (drought).[11] In what follows we pool data across these subarms.

We used a BDM approach to auction off the insurance product in the game. After receiving instructions, farmers stated a bid for the assigned insurance product and were asked to pick a (random) strike price from a jar with numbers (Jar C). If the bid was higher than the strike price, then the farmer purchased insurance at the strike price, or else the farmer could not buy the insurance product. Revenues in Round 2, therefore, are the sum of realized yield (multiplied by the unit price of maize) and possible insurance payouts for farmers who bought insurance and suffered losses, minus the cost of production and possibly the cost of insurance.

Round 3: Yield Realizations with Crop Insurance and Basis Risk

Before starting this round, we demonstrated the concept of basis risk to the farmer. We only focused on *negative* basis risk, exactly like we did in the narrative-based extension arm. Excluding positive basis risk may have consequences for how farmers value the insurance product as the beneficial effects of positive basis risk may attenuate the adverse effects of negative basis risk. Shin et al. (2022) show that under cumulative prospect theory, positive basis risk will increase demand. However, if insurance is a financial product that is first and foremost supposed to transfer resources from good to bad states, positive basis risk may have similar negative effects on demand as negative basis risk (as found for instance by Vosper and Cecchi 2023). Since we were underpowered to have a separate treatment arm to study the impact of positive basis risk, we present a simplified experiment (and narrative) that only features negative basis risk.

We used a jar with 10 beads (Jar D), blue and green, to illustrate basis risk. Drawing a blue bead implies that the farmer does not receive a payout, even if she suffered a production loss. We varied the number of blue beads in Jar D across farmers to vary exposure to basis risk. We use three levels of basis risk: 5%, 10%, and 15%. For the 5% basis risk scenario, we included either 9 or 10 green

[9]Smallholder farmers spend about 10,000 shillings on land preparation, planting, buying seed, and planting fertilizer (e.g. Kirimi et al. 2018).

[10]This meant that a farmer in the "multiple peril" insurance did not receive any payout if the deviations from the mean were not major (−1 or −2 bags of maize).

[11]The rationale behind introducing this variation was to test if it would be confounded with nonperformance and thus lead to a lower valuation for the insurance that excluded completely one type of shocks. We do not find such difference in valuations, indicating that participants on average assigned a similar value to these actuarially similar products, which we treat as one throughout the rest of this paper.

beads (1 or 0 blue beads), with equal probabilities. The farmer did not know the exact number of blue beads in the jar.[12] The probability of receiving a payout for the farmer was 95% (i.e., a 5% chance of not receiving a payout). Similarly, for the 10% basis risk scenario we included 8 to 10 green beads in the jar (equal probabilities), and for the 15% basis risk scenario we included 7 to 10 green beads in the jar.[13] The aim of the exercise was to demonstrate that basis risk is a probabilistic event with ambiguous probability and to foster learning by "doing" (experiencing the basis risk outcome).

In Round 3, farmers decided whether to purchase insurance or not (as in Round 2) and determined their yield outcomes (as in round 2). Next, they determined their realization with respect to basis risk. Farmers who did not purchase insurance, because they bid below the strike price in the BDM auction, also took part in the basis risk exercise—they learned what would have happened had they been covered by insurance, but did not experience the actual disappointment of basis risk.[14] Revenues from this round were the sum of realized yield multiplied by the price per bag of maize and potential payouts from insurance (for farmers who bought insurance and suffered losses but who did not incur basis risk) minus production and possibly insurance costs. After playing the three rounds, one round was randomly selected for making the actual payout.

2.3 | Dependent Variables: Knowledge and Insurance Demand

We have two types of dependent variables. First, we asked farmers from both the control and treatment groups to participate in a knowledge quiz. We asked 15 knowledge questions about index insurance and basis risk, and our main knowledge variable is unweighted composite score of these 15 questions, normalized using the mean of the control group (see Online Appendix Section B1). We also explore whether the individual questions contribute equally to the overall knowledge score. We use a random forest machine learning algorithm to identify the knowledge questions that mattered most (see details in the Online Appendix Section B3). Results from the random forest are corroborated with those from other algorithms, namely least absolute shrinkage and selection operator (lasso), decision tree, and k-nearest neighbors.[15] The main questions cover whether a farmer always receives a payout when they purchase insurance (sure payout), basis risk (basis risk knowledge), and the assessment of losses (loss assessment). In what follows we will also explore whether responses to these specific questions are affected by the interventions.

In addition to the effect of our interventions on "learning" (or knowledge), we are also interested in the impact on "demand for crop insurance". To measure this in an incentive-compatible manner, we offered all farmers to choose between a 200-shilling insurance discount voucher (for insurance in the approaching maize season) or an immediate cash offer. We presented each farmer with three choices involving three cash offers (KSh.50, KSh.100, KSh.150), of which one choice would be effectuated (randomly determined).[16] The discount voucher covers the minimum allowed sum of insurance coverage but can also be used to obtain a 200-shilling discount on the premium for a larger sum insured. Considering a weather index insurance that covers production costs and charges a premium of 10%, the 200 shillings voucher buys insurance worth KSh. 2000, which is about the cost of improved seeds to plant an acre piece of land (Kirimi et al. 2018). The voucher could be redeemed through local agents of a known insurance company.

[12]We use either 9 or 10 blue beads to (1 or 2 green beads) to achieve an average of 5% basis risk $(1 - (9/10 + 10/10)/2)$.

[13]The reason to not disclose the exact number of blue beads, even though farmers have an expectation of the number of blue beads, is to maintain a degree of ambiguity with regards to the true probability of basis risk, which is by definition ambiguous (if it could be precisely measured, it could be captured by an improved insurance product).

[14]For us, what matters most is that they had to take basis risk into consideration in their valuation of the insurance uptake decision.

[15]Results from all the algorithms show that knowledge about whether the farmer always receives a payout after purchasing insurance, knowledge about basis risk, and how losses are assessed caused the greatest variation in the knowledge about crop insurance.

[16]These values were determined in a pilot; not too low or too high. 1 USD dollar was equivalent to 110 Kenyan shillings at the time of the experiment.

2.4 | Data, Household Survey Summary, and Balance

Data collected during the household survey include sociodemographic controls and farming variables: age of the farmer, household size, amount (in kilograms) of inorganic fertilizer used per acre, number of years of farming (experience), education, number of pieces of land owned by the farmer, fertilizer use, type of fertilizer used, experience with insurance (including health, car, and motor bicycle), main occupation, source of seeds, and maize farm size. We also collected data on behavioral factors that we suspected to correlate with demand for crop insurance, namely optimism bias (Sharot 2011), prudence (Deck and Schesinger 2014; Trautmann & Kuilen 2018), risk aversion (Shin et al. 2022) and locus of control (Lefcourt 1991).[17] We use the least absolute shrinkage and selection operator (LASSO) to select the most relevant controls to explain variation in our dependent variables (knowledge and demand for insurance), but obtain very similar results when applying a double-postselection LASSO (not shown).[18] Table 1 summarizes the variables that "survived" the LASSO for both the knowledge and demand for insurance outcomes.

There are a few differences across experimental arms. For example, we find differences in whether the farmer had a college education ($p = 0.029$) and used fertilizer ($p = 0.052$). But the differences are small in number and magnitude. In some models we estimate below we control for the relevant covariates (those retained after the LASSO). We also did a joint orthogonality test to see if treatment correlated with the covariates. We fail to reject the null hypothesis that covariates and treatment are independent: $p = 0.125$ for the model explaining variation in knowledge and $p = 0.257$ for the model explaining variation in demand for insurance.

3 | EMPIRICAL STRATEGY AND MODEL SPECIFICATION

We examine the effect of our treatments on knowledge levels by estimating the following model:

$$K_i = \alpha + \beta_1 Narrative_i + \beta_2 Game_i + \beta_3 X_i + \beta_4 B_i + \epsilon_{1i} \tag{1}$$

where K_i is the knowledge score for farmer i, Narrative and Game capture assignment to the two treatment groups, and X_i and B_i capture demographic and behavioral factors, respectively, that survived the LASSO procedure. Coefficients β_1 and β_2 represent the average effects of the narrative information treatment and the game treatment on knowledge. We test the null hypotheses $\beta_1 = 0$ and $\beta_2 = 0$, and also the hypothesis $\beta_1 = \beta_2$. We then do a robustness analysis by re-estimating equation (1) but now replace the normalized knowledge score by each of the main questions contributing to knowledge as the dependent variables. This enables ascertaining whether the treatments influenced how farmers answered these questions.

Next, we explore the effect of the two treatments on demand for insurance, for which we use an interval regression as in equation (2).

$$Y_i = \alpha + \sigma_1 Narrative_i + \sigma_2 Game_i + \sigma_3 X_i + \sigma_4 B_i + \epsilon_{2i} \tag{2}$$

[17] See appendix (Table A6) for more details for a description of the selected control variables.

[18] Cilliers et al. (2024) argues that the two approaches typically produce rather similar coefficients, but that the double-LASSO is more appropriate if attrition is high and covariates are correlated with the treatment. Both are not true for our experiment. Out of 1409 farmers participating in the survey, 1331 farmers also participated in the experiment, for an attrition rate of 6%. Attrition was independent of treatment (see Appendix Table A5).

TABLE 1 Description and balance of variables selected for regression analysis.

Variables	Overall $N = 1331$	Control $N = 331$	Game $N = 667$	Narrative $N = 333$	p-value
Continuous variables					
Experience with insurance	2.09 (1.94)	2.03 (1.89)	2.09 (1.96)	2.16 (1.96)	0.278
Pieces of land owned	2.09 (1.35)	2.07 (1.27)	2.13 (1.39)	2.05 (1.35)	0.985
Household size	5.15 (2.45)	5.16 (2.25)	5.24 (2.54)	4.97 (2.43)	0.278
Amount of organic fertilizer	1.01 (3.26)	1.16 (4.14)	0.81 (2.15)	1.24 (4.00)	0.344
Categorical variables					
Male	602 (45.2)	144 (43.5)	292 (43.8)	166 (49.8)	0.034
Wanted insurance for next season	538 (40.4)	127 (38.4)	275 (41.2)	136 (40.8)	0.635
Wanted insurance immediately	210 (15.8)	52 (15.7)	105 (15.7)	53 (15.9)	0.978
Uses seed from previous harvest	237 (17.8)	48 (14.5)	136 (20.4)	53 (15.9)	0.995
University education	31 (2.3)	9 (2.7)	16 (2.4)	6 (1.8)	0.287
College education	93 (7.0)	14 (4.2)	50 (7.5)	29 (8.7)	0.029
Secondary education	352 (26.4)	87 (26.3)	179 (26.8)	86 (25.8)	0.741
Age 46–55	320 (24.0)	74 (22.4)	162 (24.3)	84 (25.2)	0.238
Farming and other occupations	7 (0.5)	0 (0.0)	3 (0.4)	4 (1.2)	0.038
Farmer uses fertilizer	1072 (80.5)	272 (82.2)	517 (77.5)	283 (85.0)	0.052
Interest in insurance at baseline	1239 (93.1)	313 (94.6)	626 (93.9)	300 (90.1)	0.048
Not sure when to take insurance	277 (20.8)	75 (22.7)	148 (22.2)	54 (16.2)	0.107
Access to weather information	833 (62.6)	200 (60.4)	412 (61.8)	221 (66.4)	0.106
Purchases seed	1069 (80.3)	275 (83.1)	519 (77.8)	275 (82.6)	0.717
Age 26–35	177 (13.3)	35 (10.6)	99 (14.8)	43 (12.9)	0.611
Technical education	62 (4.7)	19 (5.7)	26 (3.9)	17 (5.1)	0.73
Farmer uses organic fertilizer	182 (13.7)	39 (11.8)	96 (14.4)	47 (14.1)	0.603
Farmer uses inorganic fertilizer	516 (38.8)	134 (40.5)	252 (37.8)	130 (39.0)	0.815

Note: Values are in means for continuous variables and standard deviations in parentheses, and frequencies and percentages in parentheses for categorical variables. p-values were estimated using *xbalance* function in the R language. The function calculates standardized differences for stratified comparisons.

where Y_i is the price interval at which the participant preferred cash over the insurance discount,[19] and the other variables are as before. We test the null hypotheses $\sigma_1 = 0$ and $\sigma_2 = 0$, and also the hypothesis $\sigma_1 = \sigma_2$.

Finally, we aim to improve our understanding of the mechanism that drives changes in demand for insurance by undertaking causal mediation analysis (Celli 2022). Causal mediation analysis breaks the total treatment effect into two components, direct and indirect. The indirect effect is through an intermediate, endogenous variable, known as the mediator, which stands in-between the causal pathway of the intervention and the outcome variables (Imai et al. 2011). Denote Y_i as our outcome variable (the price interval), T_i as the treatment dummy for farmer i, and $M_i(t)$ as the potential value of a mediator variable M under treatment status t. Following Imai et al. (2011) the total treatment effect is given by:

[19]We had four groups namely, 0–50, 50–100, 100–150, 150–200. 0 and 200 are lower and upper bounds that we introduce for the interval regression. We also transformed the cash offers into their natural logs.

$$\tau_i = Y_i(1, M_i(1)) - Y_i(0, M_i(0)). \tag{3}$$

The indirect effect for individual i is defined in equation (4), the average direct effect (ADE) in equation (5), and the total effect is given by equation (6). We are interested in δ_i, the average causal mediation effect (ACME).

$$\delta_i(t) = Y_i(t, M_i(1)) - Y_i(t, M_i(0)), \tag{4}$$

$$\varphi_i(t) = Y_i(1, M_i(t)) - Y_i(0, M_i(t)), \tag{5}$$

$$\tau_i = \delta_i + \varphi_i(1-t) \tag{6}$$

We conduct the mediation analysis with one mechanism in mind, namely increased knowledge, and also control for farmers' experiences with basis risk in the game for the subsample of farmers in the Game treatment. We use the approach suggested by Imai et al. (2011). Since our mediator is a posttreatment variable, the requirement is that both the treatment and the mediator be "ignorable": This is known as the sequential ignorability assumption. This assumption, represented by equations (7) and (8), implies that the treatment is independent of pretreatment variables, and that there are no unmeasured pretreatment and posttreatment covariates confounding the relationship between knowledge (the mediator) and demand for insurance (the outcome), and that these covariates are not affected by the treatment (Imai et al. 2011):

$$\{Y_i(t', m), M_i(t)\} \perp\!\!\!\perp T_i \mid X_i = x, \tag{7}$$

$$\{Y_i(t', m) \perp\!\!\!\perp M_i(t) \mid T_i = t, X_i = x. \tag{8}$$

The first assumption is attained through randomization, but this is not necessarily true for the second criteria. To test whether this assumption is violated we follow two steps in the mediation analysis: (i) we estimate equation (1), the mediator equation; and (ii) we estimate equations (9) and (10). In (10) we separate in the game treatment the two subtreatments with exogenously greater likelihood of being exposed to basis risk (*Basis*). All other variables are as in equation (2).

$$Y_i = \alpha_c + \varphi_1 Narrative_i + \varphi_2 Game_i + \varphi_3 K_i \ + \varphi_4 X_i + \varphi_5 B_i + \epsilon_{2i} \tag{9}$$

$$Y_i = \alpha_c + \varphi_1 Narrative_i + \varphi_2 Game_i + \varphi_3 K_i \ + \varphi_4 Basis10_i + \varphi_5 Basis15_i + \ \varphi_6 X_i + \varphi_7 B_i + \epsilon_{3i}. \tag{10}$$

The sequential ignorability assumption cannot be ascertained directly, but Imai et al. (2011) suggest a sensitivity analysis based on assessing the correlation (ρ) between ϵ_{1i} and ϵ_{2i}. Correlation between the error terms occurs when there are omitted variables in the two equations (Imai et al. 2010).[20] Under the sequential ignorability assumption $\rho = 0$, and the size of ρ shows the extent to which the assumption is violated.

4 | RESULTS

We now present the empirical results. We ask first whether playing the game increased knowledge about crop insurance. Second, we examine whether game and narrative extension influenced

[20]The reliability of the use of error correlations has been questioned (Imai et al. 2010). However, all the other alternative approaches suffer from similar challenges (Qin & Yang 2021).

TABLE 2 Effect of the game and receiving information on knowledge.

	(1) Overall	(2)	(3) Payout uncertainty	(4) Basis risk	(5) Loss verification
Game	0.994*** (0.059)	0.974*** (0.055)	0.652*** (0.092)	1.690*** (0.106)	1.401*** (0.112)
Narrative	0.877*** (0.065)	0.840*** (0.062)	0.481*** (0.105)	1.303*** (0.115)	1.267*** (0.124)
Mean of control	8.338	8.338			
Additional controls	No	Yes	Yes	Yes	Yes
*Game = Narrative F-test p-*value	0.038	0.012	0.059	0.000	0.149
Number of observations	1331	1331	1331	1331	1331
Adjusted R2	0.329	0.416			
AIC	3177.3	3003.0	1634.1	1362.7	1413.3
Log likelihood			−788.072	−652.326	−677.642

Note: Control variables are experience with insurance, pieces of land owned, university education, college education, secondary education, farmer uses fertilizer, age 46–55, purchased seeds, farming plus other occupations, organic fertilizer, and seed from previous harvest, and wanted insurance in the next season. The standard errors (in parentheses) are robust, clustered at sub-location level. The *F*-test *p* value shows whether the game and narrative coefficients are statistically different. Results are robust when we (do not) control for unbalanced covariates (see details in Section C4 of the Appendix).

***$p < 0.01$.**$p < 0.05$.*$p < 0.1$.

demand for insurance. We then turn to the mediation analysis, which explores whether (how) knowledge and exposure to basis risk influenced demand for insurance.

4.1 | Effect on knowledge

Table 2 shows how the two extension modalities affect farmer knowledge. Models (1) and (2) are OLS regressions and models (3) to (5) present the marginal effects from probit regressions. In model (1) we only include treatment dummies as covariates, while model (2) includes control variables selected through LASSO. Models (3), (4), (5) are regressions with the three "main distinguishing questions" as dependent variables, as determined by the machine learning random forest algorithm. The results show that playing the game and receiving narrative information both significantly increased farmers' knowledge about crop insurance, compared to the control group. The Game modality outperforms the Narrative modality,[21] and the difference between coefficients of the game and narrative treatments (0.14 SD) is statistically significant different from zero ($p = 0.012$).

Results from models (3), (4), and (5) show that farmers in *Game* and *Narrative* had a higher likelihood of answering the three main questions correctly, compared to farmers from the control group. The difference in coefficients of the Game and Narrative variables is statistically significant at 1% for the basis risk knowledge question (model 4) and at 10% for the question on certainty in payouts, but not for the question on loss verification. We also observe a difference in the percentage of farmers correctly answering the question about basis risk. Only 21% of the farmers in the control group answered this question correctly, compared to 75% and 65% of farmers in the game and narrative groups (see details in Appendix Table A4).

These findings corroborate findings from Janzen et al. (2021) and Cai and Song (2017), who also find that these extension modalities "work". Compared to Janzen et al. (2021), our "horse race"

[21]The effect of the interventions on knowledge may not be homogeneous across the study group. We provide details on this ex-post (exploratory) analysis in the appendix (see section C5 on heterogeneous treatment effects).

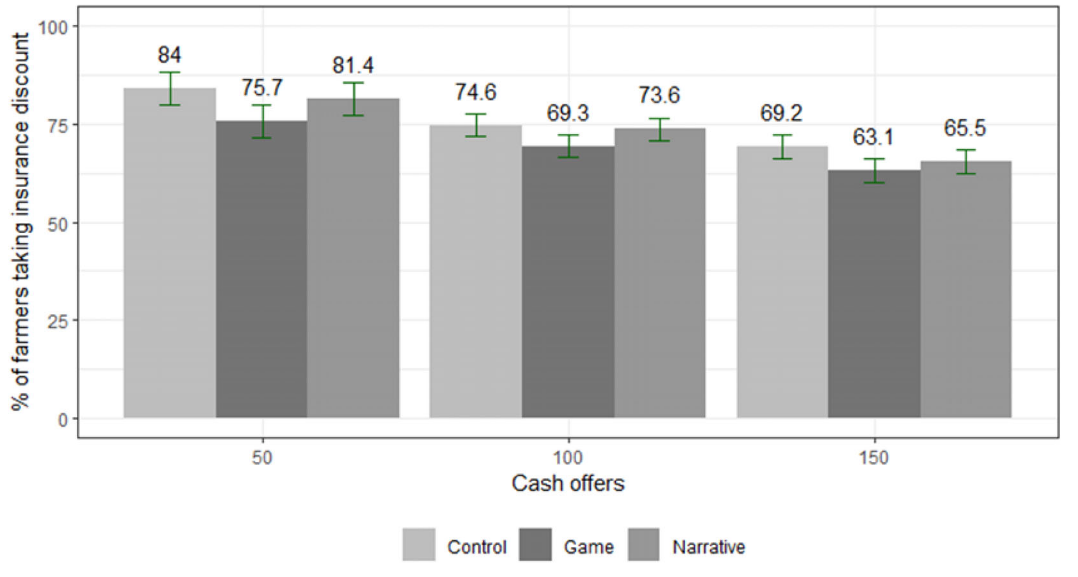

FIGURE 2 Proportion of farmers preferring cash to insurance discount.

design enables comparing the incremental effect of the game by itself, as well as the effect of each treatment relative to the pure control. Our findings show that *Game* does better in enhancing knowledge accumulation scores in contrast with findings from Patt et al. (2010) and Tessema et al. (2021) who found no difference in performance between games and conventional training. Perhaps this difference is due to the fact that our subjects (and those in Janzen et al. 2021) played an incentivized game, as opposed to the nonincentivized games in these two studies.

4.2 | Effect on demand

Figure 2 shows the percentage of farmers preferring the insurance discount over the cash offers. Not surprisingly, preference for the insurance discount decreases as the cash offer increases; this simply captures downward sloping demand for the insurance product. More interesting is that the percentage of farmers preferring the cash offer is consistently higher for experiential learning participants than for the other two groups, across all cash offers. This suggests the demand curve for insurance has shifted inward. The shift in the demand curve might reflect a shift in preferences: Experiencing shocks may make farmers more tolerant to risk in some domains (Finger et al. 2023).[22] We scrutinize further whether (and why) playing the game and receiving information about insurance causes this shift in demand for crop insurance. Table 3 summarizes the regression results of model explaining variation in demand for insurance.[23] Model (1) includes treatment dummies only, while model (2) includes control variables.

The regression results show that playing the insurance game had a small but significant negative effect on demand for insurance. In particular, playing the game reduces the probability that farmers choose the insurance discount by about 10 percentage points.

[22]Halevy (2015) also shows that individuals' preferences are time-variant even after controlling for implicit risk and demand for liquidity.

[23]The results are relatively the same when we use an alternative specification and are not sensitive to whether we cluster standard errors at the sublocation level or not (see more details in the appendix—Table A5).

TABLE 3 Effect of playing the game and receiving information on demand for insurance.

	(1)	(2)
Game	−0.111*** (0.039)	−0.102*** (0.037)
Narrative	−0.026 (0.043)	−0.014 (0.044)
Mean of the control	0.76	0.76
Additional controls	No	Yes
Game = *Narrative*, F-test p-value	0.038	0.038
Number of observations	1331	1331
AIC	4970.6	4957.3

Note: Control variables include household size, amount of organic fertilizer, gender (male), age 26–35, university education, farmer uses organic fertilizer, purchases seed, access to weather information, farmer irrigates maize, and interest in insurance at baseline. The standard errors (in parentheses) are robust, clustered at sublocation level. We also control for enumerator effects. The mean of the control is the average percentage of farmers who preferred the insurance voucher across the cash offers. The F test p-values show whether the game coefficient is the same as the narrative coefficient. Results are robust when we (do not) control for unbalanced covariates (see details in Section C4 of the Appendix).

***$p < 0.01$.**$p < 0.05$.*$p < 0.1$.

4.3 | Mediation analysis

Why did participating in the game have a negative effect on demand? To answer this question, we assess whether this effect is caused by a change in knowledge or whether additional factors play a role. The literature says that the role of knowledge in technology adoption is inconclusive; some studies find knowledge is an important determinant (e.g., Van Campenhout et al. 2021) and others do not (e.g.; De Brauw et al. 2018; Hörner et al. 2022). The literature on index insurance adoption found that basis risk is an important barrier to adoption (Kramer et al. 2022). We explore whether "experiencing" basis risk in the game has an independent effect on demand—over and above the effect of understanding what basis risk is (as captured by the knowledge mediator). Our experimental design implies that we have exogenous variation in exposure to basis risk.

The estimation results of (9) and (10) are in Table 4. We assume a linear demand function for insurance and treat knowledge as a mediator. In column (1) we probe the correlation between knowledge and demand, and in column (2) we add treatment dummies to test if the treatment affects the outcome after controlling for the knowledge mediator. In column (3) we introduce dummies for participating in a game treatment with "high basis risk" (10% or 15%). In column (4) we interact knowledge with the highest degree of basis risk to test if greater knowledge had a differential effect when exposed to greater likelihoods of basis risk (to check for a violation of the sequential ignorability assumption).

Across all models we find a negative association between knowledge and the probability of choosing the insurance voucher. This result is consistent with a story where, on average, farmers tend to be optimistic about the value of index insurance, and learning about how index insurance actually works reduces the attractiveness of the insurance product. This is true for narrative-based learning and experiential learning. A one standard deviation increase in the knowledge score reduces insurance uptake by 5 percentage points. Since experiential learning is more effective than narrative-based learning, on average the demand-reducing effect of knowledge is greater for subjects in the Game treatment. Including both the knowledge variable and treatment dummies shows how knowledge mediates the treatment effects (column 2). The *Game* dummy is not statistically different from zero, and the coefficient is much smaller than before.

TABLE 4 Mechanisms analysis, extension modalities and demand for insurance.

	(1)	(2)	(3)	(4)
Knowledge	−0.042** (0.018)	−0.046** (0.021)	−0.048** (0.022)	−0.053** (0.023)
Game		−0.057 (0.043)	0.013 (0.062)	0.019 (0.064)
Narrative		0.008 (0.052)	0.009 (0.052)	0.014 (0.052)
10% basis risk			−0.069 (0.067)	−0.069 (0.067)
15% basis risk			−0.134** (0.060)	−0.161** (0.077)
Knowledge × 15% basis risk				0.031 (0.048)
Mean of the control	0.76	0.76	0.76	0.76
Additional controls	Yes	Yes	Yes	Yes
Number of observations	1331	1331	1331	1331
AIC	5073.2	5059.3	5058.5	5060.2

Note: Control variables include household size, interest in insurance at baseline, use of organic fertilizer, amount of organic fertilizer, gender (male), age 26–35, education, purchases seed, access to weather information, wanted insurance immediately, farmer was not sure when they would need insurance. The standard errors (in parentheses) are robust, clustered at sublocation level. The mean of the control is the average percentage of farmers who preferred the insurance voucher across the cash offers.
***$p < 0.01$.**$p < 0.05$.*$p < 0.1$.

But this is not all. If we introduce dummies to capture exposure to basis risk, we find that exposure to a high level of basis risk (15%) reduces demand for insurance (column 3).[24] The knowledge variable remains a significant determinant of demand, and its magnitude is hardly affected by the basis risk dummy. The demand-reducing effect of basis risk therefore appears to be over-and above the mediating effect of knowledge. Narrative-based learning and experiential learning both cause subjects to learn about basis risk and understand what it does (as is evident from the test questions), *but this is not the same as experiencing high basis risk firsthand*. This goes back to the premise of ELT, discussed in the introduction. Since farmers in *Game* have more knowledge than farmers in *Narrative*, on average, they are willing to pay less for the insurance product. Farmers in *Game* who were exposed to high basis risk further reduced their willingness to pay. Games enable subjects to learn and generate "experiences" unique to the players (Landers et al. 2019), which have an independent effect on preference formation.[25] In column (4) we interact knowledge and exposure to high basis risk. This interaction term is not significant, corroborating the validity of our mediation analysis with respect to knowledge (Imai et al. 2011).

Next, we calculate ACME and Average Direct Effect (ADE), and report results in Table 5. Without controlling for basis risk (Panel A), both the ACME, ADE and proportion mediated by knowledge are significant. The ACME explains about 44% of the total effect of knowledge on demand for insurance at 5% significance level.[26] The mediating role of knowledge on demand for insurance

[24]This negative effect is in line with earlier studies (e.g., Elabed & Carter 2015; Hill et al. 2013; Janzen et al. 2021; Serfilippi & Ramnath 2018), and is consistent with a rational valuation of the insurance (since in our experiment basis risk is only negative, it lowers the actuarial value of the insurance).

[25]Game elements such as badges, levels, leaderboards, and rewards like in our case motivate (intrinsic or extrinsic) the learner, factors that make games effective (Sailer et al. 2017).

[26]De Brauw et al. (2018) find a similar effect on the adoption of orange fleshed sweet potato among farmers in Uganda but find no causal mediation effect for farmers in Mozambique.

TABLE 5 Average causal mediation effect (ACME) and average direct effect (ADE), from the mediation analysis.

	Estimate	95% CI lower	95% CI upper	*p*-value
Panel A: Without basis risk				
ACME	−0.043	−0.08	−0.004	**0.028**
ADE	−0.058	−0.142	0.021	0.172
Total effect	−0.100	−0.178	−0.029	**0.004**
Proportion mediated	0.437	0.044	1.562	**0.032**
Panel B: With basis risk				
ACME	−0.044	−0.082	−0.006	**0.032**
ADE	0.014	−0.102	0.133	0.780
Total effect	−0.030	−0.133	0.079	0.570
Proportion mediated	0.530	−10.823	8.495	0.582

Note: CI is the confidence interval, while proportion mediated is the percentage of the ACME as a fraction of the total effect.

persists after controlling for basis risk (Panel B). The ACME is significant at 5% and explains 53% of the total effect.

Next, we conduct a sensitivity analysis as suggested by Imai et al. (2010) to test whether the causal mediation effects are robust to the sequential ignorability assumption. As mentioned earlier, this analysis assesses whether there are omitted confounders between the outcome and mediator equations by considering the correlation (ρ) between the error terms of two equations. We estimate ACME over the whole range of ρ (-1 to 1), which has both conceptual and practical limitations (Keele et al. 2015). There is no accepted threshold to judge whether a result is "unacceptable" and the analysis supports only a limited number of mediator-outcome model combinations. For this reason, we do not use our preferred models (see Section C4 in the Appendix), so the results we present are "conservative." We visualize the findings from the sensitivity analysis in Figure 3 (panel B is a zoomed in version of A). The results show that ACME is less than -0.1 when $\rho = 0$, implying that our results are sensitive to small changes in ρ.

5 | DISCUSSION AND CONCLUSIONS

Lack of information is an important explanation for imperfect technology adoption by small scale farmers (Takahashi et al. 2020). One strategy suggested in the literature to promote the adoption of innovations is to increase the effectiveness of informational interventions (Bridle et al. 2020; Suri & Udry 2022). This can be achieved through pioneering alternative approaches in delivering information to farmers, other than the conventional descriptive extension modality (Kaiser & Menkhoff 2022). Game-based learning is one such approach. Though games have been used a few times to educate farmers, there is a paucity of evidence on their effectiveness vis-à-vis conventional training approaches. This ambiguity concerns both the impact of experiential learning on knowledge levels and subsequent behavior, including technology adoption.

We use a framed field experiment with an incentive compatible game component in one of the treatments to test whether (i) games are superior in enhancing knowledge compared to conventional narrative-based approaches, (ii) information transfer affects demand for index insurance, and (iii) experiences during the game affect demand for insurance after the experiment. We find that the framed insurance experiment we designed is superior to narrative information in enhancing knowledge. Compared to the control group, both approaches increase knowledge by approximately one standard deviation, so both approaches help farmers to understand complex concepts such as crop insurance and basis risk. However, experiential learning outperformed the narrative-based approach:

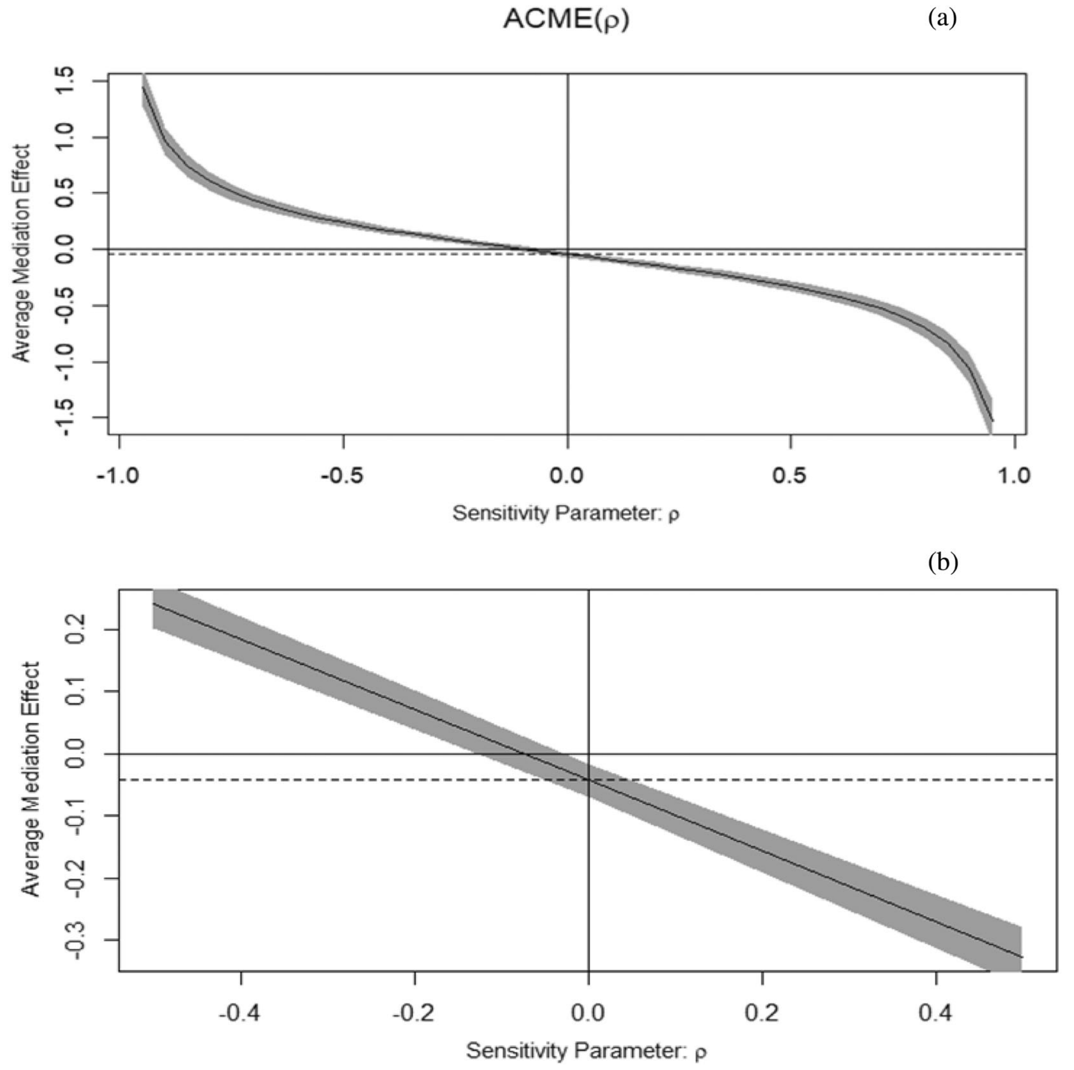

FIGURE 3 ACME as a function of **ρ**. The broken line represents the ACME when ρ is zero, the gray regions show the 95% confidence interval for ACME at different values of ρ, and the solid line is the ACME at each value of ρ.

playing the insurance game not only helps to accumulate knowledge but also generates experiences that deepen the learning process and raise awareness of possible nonperformance of the insurance product.

Unlike narrative-based learning, we find that game-based learning significantly influenced demand for insurance—and the net effect was negative. Higher knowledge levels are associated with reduced demand, and experiences with high basis risk during the game push down demand further. In theory, the impact of experiential learning on adoption is ambiguous, depending on prior understanding of the product and expectations with respect to its performance. In our case, the net effect was negative as farmers better understood and operationalized the concepts of basis risk and its adverse consequences than before the game. Our results underscore the need of addressing basis risk in index-based insurance products and the need to design products that cover the most important risks of the farmer to increase the relevance of the products for farmers seeking to manage their production risks.

Our paper is close to Janzen et al. (2021), who also study experiential learning and demand for insurance. They find that conditional on being offered high basis risk insurance, playing their game increased demand, whereas playing their game had no effect on demand conditional on being offered low basis risk insurance. Conditional on not playing the game, being offered low basis risk insurance increased demand. The authors refer to this counter-intuitive result as "surprising" and rationalize it by arguing that the low basis risk product may have performed worse than expected by the farmers and the high basis risk product may have performed better than expected.[27] An important difference between that study and ours is that farmers playing the game in Janzen et al. (2021) first participated in a narrative-based learning session, and therefore were "primed" to form expectations about the insurance product and exposure to basis risk. In contrast, farmers in our game did not receive narrative-based extension and, hence, were not challenged to form such expectations prior to playing. They simply experienced low or high basis risk during the game and proved able to differentiate their valuation based on their level of exposure. Sensitivity to exposure to basis risk was evident during the follow-up demand revelation exercise. Another difference between Janzen et al. (2021) and this paper is that their valuation exercise is based on stated preference while we use an incentive-compatible approach to measure preferences for actual products after the game.

Learning about the advantages and disadvantages of insurance products, like other agricultural technologies, can take a lot of time in "reality" (Maertens et al. 2021). The results of this paper extend well beyond the domain of insurance. In fact, while the sign of the effects observed in our study may be unique to some characteristics of index insurance, the mechanism through which we observe changes in demand applies to the adoption of any innovations in farm production. Learning through on-farm experimentation may involve (opportunity) costs and could be misleading depending on the sequence of signals that farmers receive about performance (varying with the weather, etc.). Incorporating carefully designed experiential learning elements has the potential to reduce the cost associated with experimentation and can generate "real life" experiences in a shorter time (e.g., Tjernström et al. 2021). Insights from how farmers behave in games can subsequently be used to improve innovations, focusing on those features that matter most to farmers. Of course there are also costs, especially in the short run, associated with using games as extension tools. The implementation of game-based learning requires additional training of extension officers, so governments and donors could consider allocating additional resources to employing and training extension agents. Alternatively, an enabling environment could be created within which the private sector provides such extension services (Dar et al. 2024).

Our study is not without limitations. Our approach to game-based or experiential learning, particularly concerning knowledge accumulation, is relatively broad. We rely on an extrinsic incentive mechanism: a financial incentive provided outside the game itself, although based on within game decisions. Intrinsic incentive mechanisms, embedded directly within the game, such as points, badges, leaderboards, and levels, may impact both knowledge accumulation and player motivation differently. Further exploration of these embedded incentives and their effects is needed to fully understand the rubrics of game-based/experiential learning. Additionally, we do not examine whether experiential learning creates a lasting knowledge effect (and for how long) compared to a narrative-based intervention. Evidence shows that knowledge (experience) from information interventions fades with time (e.g., Hoffmann et al. 2021). Assessing knowledge over a longer period would offer additional insights into the cost-effectiveness of game-based learning as an alternative extension tool.

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[27] They develop a model with reference-dependent learning and loss aversion, resulting in misattribution bias.

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SUPPORTING INFORMATION

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

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