Highlights

Digital technologies can scale the study of adaptation in small-scale fisheries

Anonimized

- We develop and test a new method to deploy behavioral economic experiments by leveraging digital media platforms: "digital experiments"
- These digital economic experiments elicit and capture responses that are qualitatively similar to those through in-person games, but at a fraction of the cost
- Even when fishers were informed about the risk of an environmental shock at the onset of the experiment, adaptation ensues only after a shock has occurred, and the effect dissipates quickly.

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Abstract

Economic experiments have led to important advances in our understanding of human adaptation in coupled social-environmental systems. However, economic experiments may be costly, which limits their scale and even the external validity of their results. Digital technologies offer great potential to deploy economic experiments at scale, but this approach remains largely untested. Here, we evaluate the feasibility of using mobile computing platforms (smartphones, tablets, and computers) to deploy digital economic experiments that collect fishers' response to environmental shocks. To do so, we developed a digital version of a well-studied natural resource harvesting game characterized by a renewable common-pool resource that is harvested in repeated iterations, and used social media platforms to attract users (fishers). We recorded total of 3,369 interactions with the outreach material, which lead to a total of 740 rounds played. We show that fishers' behavior during digital experiments was qualitatively similar to responses observed during in-person games reported in the literature. Additionally, we find that providing information about the risk of environmental shocks alone is not sufficient to induce adaptation by fishers, who only adapt by reducing their harvest rates after experiencing a climatic shock.

Keywords: Climate hazards, Adaptation, Climate change, social-ecological systems, Human dimensions of environmental change

1. Introduction

Coastal and inland small-scale fisheries and aquaculture produce half of the global fish catch and over two-thirds of aquatic food production for human consumption, providing livelihoods to 100s of millions of people as well as critical nutrition to approximately 1 billion people [1]. As with other food systems, the economic productivity and stability of the wild-caught fisheries sector is subject to the forces of economic markets and national policies [2, 3]. However, unlike other food systems where humans may control some inputs, processes, and outputs, the productivity of fisheries remains largely constrained by the environmental, ecological, physiological processes [4, 5, 6].

Consider the example of agriculture, where a farmer may select their crop, when to plant it, how much fertilizer, pesticide, and water to use, and when to harvest so as to maximize returns. They may also build reservoirs to water plants in the dry season, and greenhouses to control light, temperature and humidity, or provide their plants with shade to fight rising temperatures. Fishers, on the other hand, have little to no control over the factors that drive somatic growth, natural mortality, per-capita fecundity, reproductive output, early (larval) development, movement and migration of wild fish [e.g. water temperature, dissolved oxygen, [7, 8], and food availability [9, 10, 11]]. This inability to control some determinants of a system's productivity (in magnitude, space, and time) makes wild-caught fisheries (particularly small-scale) disproportionately vulnerable to the adverse consequences of climate change. Therefore, understanding how fishers respond to climate change and environmental shocks, and what triggers transformations and boosts adaptive capacity is a priority to ensure social-economic sustainability of fisheries, as well as for food security and nutrition of the coastal communities whose health and well being depend upon the exploitation of marine, renewable resources, particularly in low and mid-income nations [12].

One of the main challenges to designing and implementing adaptation-enhancing policies for small-scale fisheries is their dynamism and diversity (in size, targeted species, composition, identity, and management regimes [12]). Economic experiments, a method from experimental economics, provide effective frameworks for understanding these complex dynamics and behaviors. Economic experiments are "games" designed to mimic real-life decision-making incentives under a controlled environment, where the researcher can credibly introduce an exogenous treatment (*e.g.* "if a 6-sided dice rolls 1, you lose 50% of your stock") and, while maintaining everything else constant, elicit and record a player's behavioral response (*e.g.* "I already lost 50% of my stock, so I shall harvest less (or more?) this round"). These approaches have been widely used in the literature because they allow testing how different factors of the game affect decisions and, under certain conditions, may indicate how fishers will respond to similar factors in the real world (See [13] for an analysis on the role of framing and external validity of games). For example, Finkbeiner et al. [14] conducted economic experiments with fishing cooperatives in Baja California (Mexico) and found that fishers adapted to environmental uncertainty or illegal fishing -both causing a sudden decline in the stocks- by voluntarily reducing their catch rates, and that these adaptive responses were stronger in communities where fishers stated trust in management institutions and secure fishing rights.

These methods have also been used to study trust [13], competition [15], and gender-specific responses [16], among many other relevant topics that have made important contributions to the study of social-ecological systems. However, economic experiments can face three limitations: 1) they require large upfront and continued financial resources to gather players and researchers in a room; 2) they often employ small sample sizes that only represent a small subset of fishers; and 3) they may have limited external validity, making it difficult to use insights from local processes to inform general policies [17]. As a result, large sums of money and valuable time are devoted to learning processes that may not translate outside the context of the focal community or fishery assessed. Digital technologies can be leveraged to overcome some (or most) of these challenges [18], as they offer untapped potential to cost-effectively reach a larger and more diverse group of fishers, thereby generating generalizable insights that can be used to inform policy.

Here, we combine digital technologies with common approaches from behavioral and natural resource economics to scale the study of adaptation across diverse fishing organizations. We designed a digital version of previously-tested, in-person, field experiments on behavioral responses to climate change and used mobile computing platforms (smartphones, tablets) to engage with fishers in Mexico. Our main objective was to evaluate the feasibility of using mobile digital platforms to deploy economic experiments. For digital game experiments to be a suitable substitute for in-person games, they must be able to overcome at least one of the three limitations stated above (*i.e.* cost, sample size, and external validity). We assessed feasibility by addressing the following two questions: 1) Can we compel enough fishers to play our digital games? and 2) Can we collect a diverse sample, representative of different fisheries, environments, and demographics? Moreover, even if the answers to both questions are positive, we must also show that digital economic experiments can elicit and capture the same behaviors and responses as in-person economic experiments would. Therefore, we also asked: 3) How do responses captured by digital economic experiments compare to those observed for equivalent in-person games? Finally, we asked 4) What new insights, with respect to what was previously found, emerge from the analysis fo the digital experiment data?

2. Methods

Our methods section is divided into two main parts. The first one focuses on our experimental design and approach to data collection. We begin with a description of the original experiment and its adaptation to the digital context. We then provide a brief description of the software development component of our project, as well as the use of social media to broadcast our game and track user engagement. The second part then focuses on the analyses made to the data, which relate to our main objectives. We first outline how we measured game engagement, we then present methods used to validate our responses, and then we introduce a new analysis where we study the timing of adaptation in relation to knowledge about and realization of shocks.

2.1. *Experimental design and data collection*

2.1.1. *The digital economic experiment*

We develop our first digital economic experiment with the objective of studying behavioral responses in the face of climate change and, specifically, climatic shocks causing massive mortality (*sensu* [19, 20, 21]). This choice is grounded on two reasons. First, because the adverse effects of climate change are one of the most pressing issues faced by fishing communities today [12]. And, secondly, because we conducted this study with the explicit goal of comparing the outcomes of game experiments fishers play through digital technology with those previously conducted in person. To this end, we replicate the dynamics of an in-person game experiment originally designed and conducted by Finkbeiner et al.[14] in Baja California (Mexico), as described below.

The original in-person game simulated a common-pool resource harvested by five fishers over 15 rounds. The stock available to these players in period t depended on extraction decisions in period $t-1$. Overall, 180 fishers from six fishing communities participated in the game. The experimental treatments relevant to our exercise were designed to test for changes in fishing behavior under factorial combinations of environmental uncertainty (climatic shock) and communication. In each round, fishers were presented with the stock size (ranging between 0 - 100) and they were allowed to fish 0-5 resource units each. After total harvests were tallied, the escapement (*i.e.* stock size minus total harvests) grew at a constant 10% rate for next round's stock size (up to maximum stock size of 100 units). When relevant, environmental uncertainty was introduced through a 10% chance of losing 50% of the total escapement each round, and communication was introduced by allowing fishers to discuss non-binding agreements on individual and aggregate-level catch. The game also included a baseline treatment of no environmental uncertainty and no communication. Fishers were paid to participate in the game, and the payouts were designed to compensate for wages earned on an average day's fishing.

For the digital experiment, we make three modifications to the design. First, we restrict our implementation to two treatments: a baseline treatment without environmental uncertainty, and a main treatment of interest with environmental uncertainty, following the same parameters as before. Secondly, each fisher still harvests a common-pool resource, but they interact with four pre-programmed virtual fishers (hereinafter also referred to as bots) harvesting the same resource, rather than playing against other real-life (human) fishers. The virtual fishers were programmed following real human decisions and parameters published by [14] for each treatment (See Appendix A). This parameterization allows for random round- and treatment-specific variations in harvest levels that replicate previously observed behavior. We do not incorporate a communication treatment (*i.e.*, where players communicate between themselves) or peer-to-peer connections for fishers to play among themselves due to computational limitations (*i.e.*, we would require computationally-expensive peer-to-peer connections). In our game, fishers first play the baseline treatment (*i.e.*, 15 rounds with no climatic shocks), immediately followed by the environmental uncertainty treatment (i.e., another 15 rounds) where, at each round, there is a 10% chance of a 50% collapse of the stock. In case the fisher chose to play more games (of 15 rounds each), these were all played under the environmental uncertainty treatment. Finally, our game does not include any financial compensation or incentives because part of our objective is to see whether the game can reduce the costs of deploying experiments while simultaneously increasing sample size and external validity (but see [22] for a discussion on response rates and monetary incentives). Mathematical equations and pseudo-code are provided in Appendix A.

2.1.2. Development of the digital platform

The digital experiment uses a web-based platform, which we developed under the ShinyApps framework in R and RStudio. This provides a simple way to run R code in a remote server accessed through an HTML front end faced by fishers. The digital platform, called “La Pesca Cambiante” (*i.e.*, The Changing Fishery) is available online; the source code is openly accessible on GitHub. We assumed most players would access the game on their phones or tablets, so we developed the user interface with a portrait orientation. Upon entering the app, users are presented with a brief optional survey (details below) followed by instructions on how to interact with the controls. The main screen is designed to replicate the information available to fishers during the original treatments of the game implemented by [14].

Throughout the game, fishers could observe the total stock size with the number of specimens -represented by a simple sketch of a marine species of commercial interest– in the fishing ground, and a numeric badge indicating current population size. One of three species of commercial interest (crab, shrimp, and finfish) was randomly selected at the beginning of each round to ensure a random and diverse representation of the resources commonly targeted by fishers. Fishers could also observe the total catch by the entire group, their own previous catch, and a counter (from 0 to 15) showing the current round number. A slider allows fishers to select their catch each round (0-5, or maximum population size) and a button allows fishers to submit their harvesting intentions. When the baseline treatment was completed and fishers indicated to play the next game, they were presented with pop-up notification of environmental uncertainty and the game's color scheme was modified. Images of each screen are shown in Figure 1.

We optimized the user interface by holding two focus groups where players tested the digital platform before releasing it to the public. The first one with personnel from the civil society organization Comunidad y Biodiversidad, A.C. (COBI; n = 5 players) and the second with members of a small-scale fishing cooperative in El Rosario, Mexico (n = 5 players). These helped us develop, refine, and finalize the user interface for the digital economic experiment, but no changes were made to the underlying game dynamics.

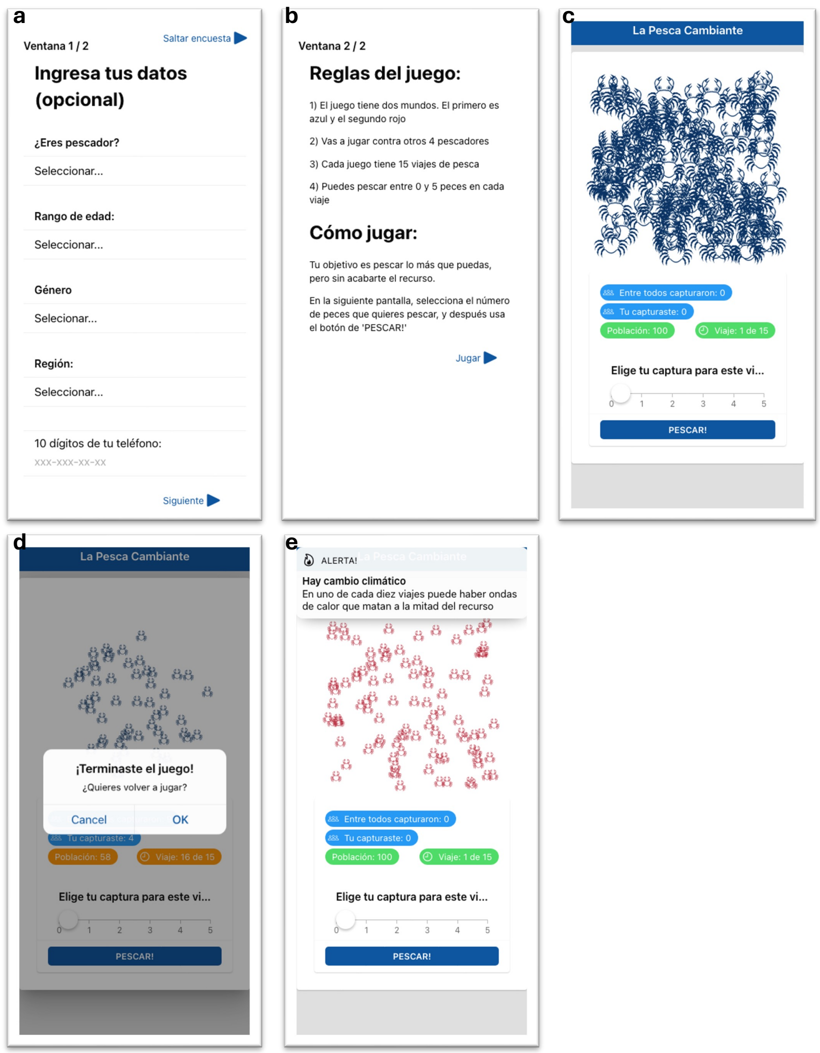

Figure 1: **Five images of different screens presented to fishers.** Panel **a** shows the welcome screen, with the brief optional survey. Panel **b** shows the instructions given to fishers. Panel **c** shows the baseline playground, with four informational badges. Panel **d** shows the end-of-game message and adoption to advance to the next game (treatment). Panel **e** shows the playground for the environmental uncertainty treatment, along with the pop-up notification. Note the change in color scheme between treatments (from blue in **c**-**d** to red in **e**).

2.1.3. Communication and outreach

Testing our ability to recruit players into the game was one of our research questions, so we followed two approaches. First, we wrote a blog post (in Spanish, available here) where we introduced the project, the objectives, and the game. The blog post contained an invitation and link to play the app. The blog post was shared through the networks (*i.e.,* FaceBook, web site, and groups) owned by PescaData, a digital logbook app for small-scale fishers. We used short video clips with a demonstration of the game (Supplementary materials Video 1 and Video 2). The second strategy bypassed the blog post, and instead the FaceBook post (posted on COBI's profile) directly linked social media users to the game. A total of four posts were promoted for 10, 13, 8, and 16 days, with promotion costs of $1000 MXN, $1200 MXN, $400 MXN, and $1200 MXN each. The total investment was $3800 MXN, or around $200 USD. We used FaceBook analytics to count the number of times people clicked on the links, and to collect basic demographic information like self-reported gender identity, age, and location. We also tracked the number of interactions with the blogpost, with the link that took readers to the game, and the extent to which users interacted with the game (*e.g.*, access, access and play one round, access and play two rounds).

2.1.4. Tracking engagement and behavioral responses

For each fishers' interaction with the game, we gathered data on the type of treatment, the round number, population size, individual harvest, aggregate harvest, escapement, and indicators for catastrophic mortality (if relevant), as well as the data gathered in the optional survey (Figure 1A). This data, stored in a google spreadsheet with a unique (anonymized) identifier, is comparable to the one generated by the original in-person game experiments with which we will compare our results.

2.2. Data analysis

We performed a survival analysis to derive the proportion of fishers that made it from one stage to the next. We counted the number of interactions at each of the following stages: Social media post, blog post, entering the game, playing at least one treatment in the game (*i.e.*, baseline), and playing at least two treatments in the game (*i.e.*, baseline and environmental uncertainty). We calculated the proportion of interactions flowing from one step to the other, and also generated an overall survival matrix to show pairwise comparisons of proportions of players between the stages above.

2.2.1. Measuring engagement

We followed a similar approach to [14] and tested for changes in harvest behavior between treatments. The original analysis used average group catch as a fraction of maximum catch as the response variable. Here, since only one player per game is human (the other four being virtual fishers or bots), we use player-level catch as a fraction of maximum player-level allowable catch for each round as our response variable. We are interested in two parameters: 1) the slope of catch over time and 2) the difference in catch rates across treatment status. We estimate these parameters of interest using a linear regression of the form:

$$y_{i,t} = \beta_0 T_t + \beta_1 D_i + \boldsymbol{\mu} + \epsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is the catch rate of player i at round t, β_0 captures the change in catch rate through rounds (T_t), and β_1 captures the change in catch rate when player i faces the environmental uncertainty treatment (*i.e.*, $D_i = 1$). We include fixed-effects by region captured by vector $\boldsymbol{\mu}$, and implement Driscoll-Kraay standard-errors [23]. Note that we only analyze responses by human fishers, never by bots. We also perform robustness tests restricting the sample to sessions where the players played both the baseline and treatment rounds, and when they only played the baseline round. All regressions were performed using the fiexest package (v0.12.0; [24]), running in R version 4.4.0 (2024-04-24) and RStudio 2024.04.0+735 [25].

2.2.2. Validation of behavioral responses

Finkbeiner [14] showed that when fishers became aware of environmental uncertainty, they reduced their catch rates; this behavioral response was more pronounced for those who perceived to have been more exposed to environmental change in the real world. But do they do it as soon as they are made aware of the possibility of a shock, or only once they have experienced a shock? To answer this question we extend the previous analysis by testing for the timing of the behavioral response taken by fishers. We first estimate the same model as before, but restrict the sample to all rounds leading up but not including the round in which the first shock ensued. Thus, this sample only contains activity where players were aware of the environmental uncertainty, but they had not yet experienced it in the game. A negative $\hat{\beta}_1$ would indicate that knowledge of environmental uncertainty alone is enough to induce an anticipatory behavioral change (*i.e.*, reduction in catch rates).

We then extend the analysis under an event-study framework, where we look at player-level changes in behavior immediately before and after the shock is delivered, to assess if and how behavior changes after an actual shock, not an anticipated one, occurred. Here, the estimating equation takes the following form:

$$y_{it} = \boldsymbol{\beta_t} T_t + \alpha_1 Pre_t + \alpha_2 Post_t + \boldsymbol{\omega} + \boldsymbol{\tau} + epsilon_{it} \tag{2}$$

Where y_{it} is still our response variable measuring the catch rate of player i at time t, $\boldsymbol{\beta_t}$ estimates a vector of dynamic treatment effects corresponding with time-to-treatment as indicated by the vector of dummy variables T_t (between -5 and 5). Coefficients α_1 and α_2 estimate the effect of dummy variables that aggregate the effect of observations more than 5 rounds before (Pre_t) and after ($Post_t$) from the time of treatment. Finally, $\boldsymbol{\omega}$ and $\boldsymbol{\tau}$ are unit- and time-fixed effects. Our supplementary materials include a series of robustness tests where we estimate the same model without α_1 and α_2 and expanding T_t to the full range of the data, or where we use the robust two-way fixed-effect estimator proposed by Sun and Abraham [26].

2.2.3. Assessing the effects of shocks on behavioral responses

3. Results

3.1. Summary statistics of user interactions

Web analytics data show large engagement in all states throughout Mexico, with a total of 3,369 clicks on the link taking viewers to the blogpost Figure 2a. The largest number of social media interactions with the social media posts were recorded for the state of Sonora (657 interactions), one of Mexico's most important states in terms of fisheries production. Veracruz, Baja California, Chiapas, and Yucatán round-up the top-five states with large engagement numbers at 592, 491, 490, and 469, respectively. The bottom-five states were Aguascalientes (22), Querétaro (28), Tlaxcala (37), Nuevo León (48), and Baja California Sur (56) (note that the bottom four are landlocked states or states where fisheries are not a primary economic activity). There were 14 (0.38%) instances where the state could not be identified. Demographic data suggests that the posts receive the most interaction from men, especially those between 25 and 45 years of age (Figure 2b). The female modal age was lower, with 18-34 years of age being the largest portion.

Traffic analytics data show that 55 people accessed the game. Of these, 21 completed at least the first game (*i.e.*, 15 rounds without environmental uncertainty) and 11 played more than one game (*i.e.*, 15 rounds under no uncertainty and 15 rounds under uncertainty). These interactions result in a total of 740 rounds played between both treatments (N = 310 baseline, N = 430 uncertainty). Figure 3 shows a survival matrix and the cumulative growth in the number of unique users with respect to each post. Note that promotion of social media posts often resulted in corresponding increases in interactions with the game, suggesting broad promotion could be a mechanism for increasing engagement. These data suggest an end-to-end player acquisition rate (also termed "click-through rate") of 0.43%, at a cost of $345MXN (about $18 USD) per user.

3.2. Validation of behavioral responses

Time series of player behavior and stock size for digital experiments as well as previous data from Finkbeiner et al [14] are shown in Figure 4. It is visually evident that catch rates decrease through time in all cases (Figure 4a). These visual insights are corroborated by regression analy-

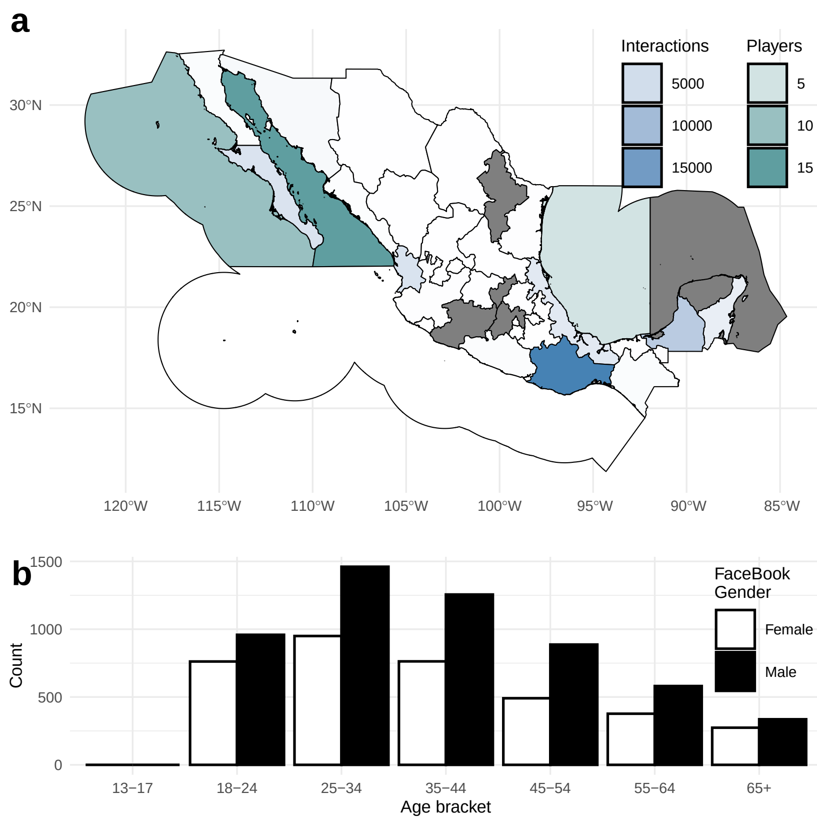

Figure 2: **Map of interactions with the FaceBook posts**. Land polygons show states in Mexico, and they are colored based on the number of interactions received in blog posts. Polygons over the ocean show Mexico's five fishing regions and are colored based on the number of players from each. Gray polygons indicate no samples.

sis of the digital experiment data, where we find that catch rates decrease significantly through time ($\hat{\beta}_0 = -0.009; p < 0.01$) and that, when faced with environmental uncertainty, fishers significantly reduce their catch rates ($\hat{\beta}_1 = -0.091; p < 0.01$). The estimate for change in catch rates through time is equivalent to that reported by Finkbeiner et al[14] (at -0.012). However, our estimate of the effect of environmental uncertainty indicates a

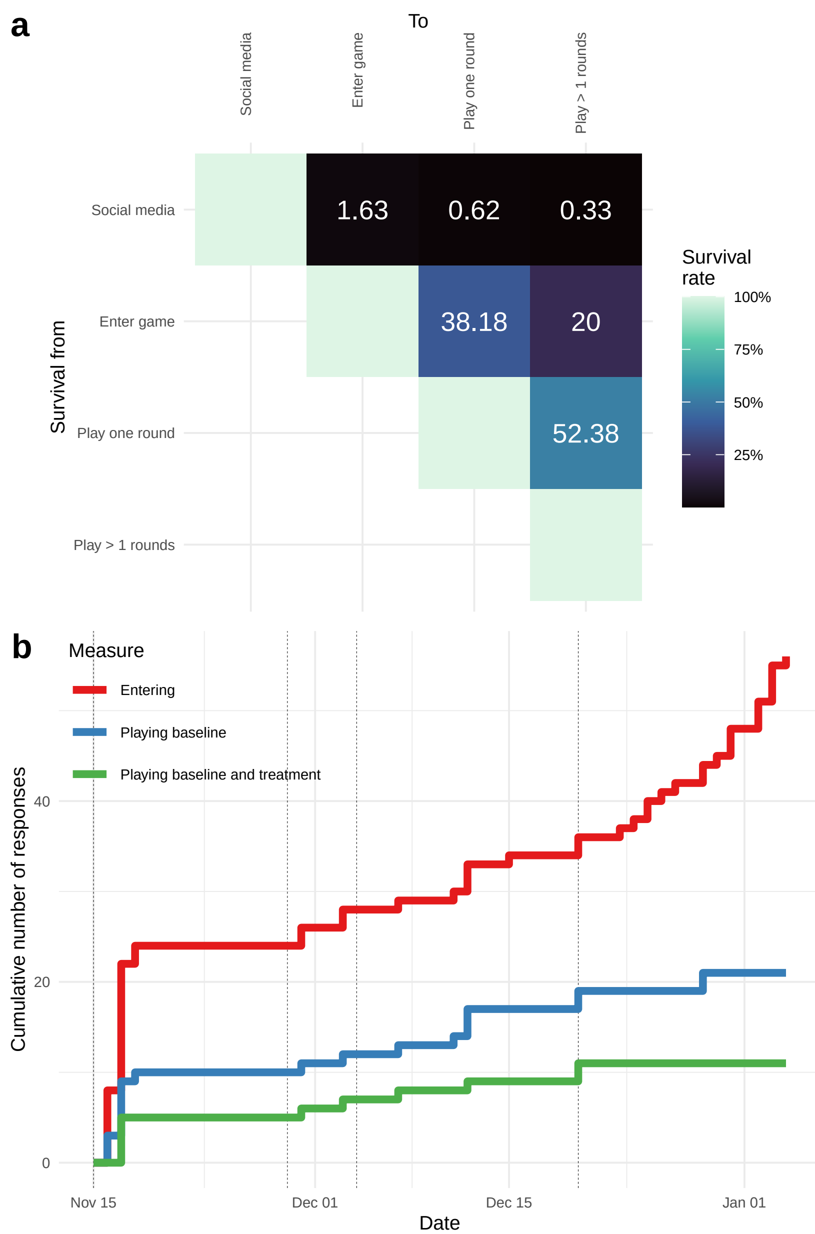

Figure 3: **Bottlenecks in user interaction and sample acquisition.** Panel **a** shows a survival matrix, where each block represents a stage and the numbers (and colors) in them show the amount of interactions. Panel **b** shows the total number of sessions where the user filled-in the survey and started the game, where at least the baseline game was played, and where the player played the baseline and uncertainty games. The dashed vertical lines indicate dates in which social media posts were posted.

stronger response by fishers, relative to what in-person experiments recorded (-0.06). Restricting the sample only to players that played both games yields a $\hat{\beta}_0 = -0.008; p < 0.1$ and $\hat{\beta}_1 = -0.102; p < 0.01$, while looking at the change in catch rate through time for those who only played the baseline treatment we find $\hat{\beta}_0 = -0.01; p < 0.01$. Figure 5 shows coefficient estimates compared to those estimated from in-person experiments [14], and Table 1A shows model summary statistics; both also show results for different subsamples as robustness tests.

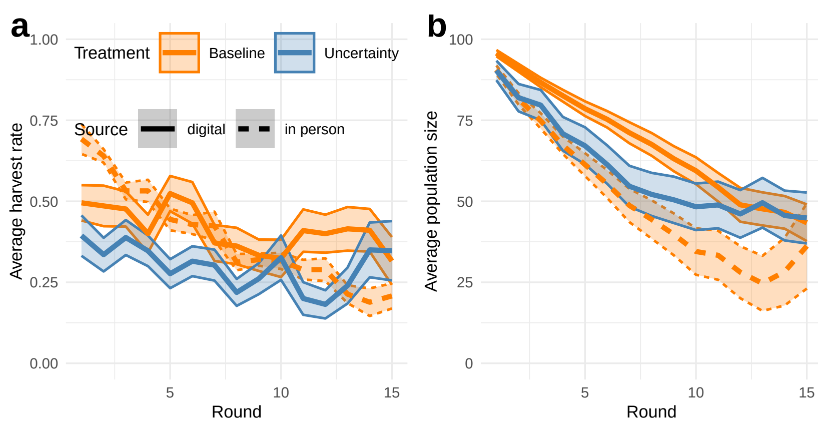

Figure 4: **Comparison of state variables in the original experiments by Finkbeiner et al [14] and the digital experiments.** Panel **a** shows change in harvest rates through time, and panel **b** shows change in population size through time. Dashed lines represent data from original in-person experiment (baseline treatment only) and solid lines indicate data from digital experiments performed here. Colors indicate the treatment.

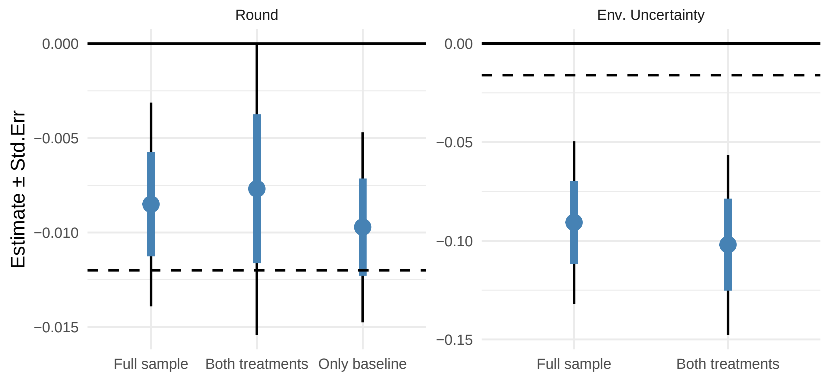

Figure 5: **Coefficient estimates retrieved from digital experiments.** The left panel shows the coefficient on time (*i.e.*, $\hat{\beta}_0$) and the right panel shows the coefficient on environmental uncertainty (*i.e.*, $\hat{\beta}_1$). Points show coefficient estimates, the blue portion of the error bars shows standard errors, and the black portion of the error bar shows 95% confidence intervals. We provide estimates for the full sample and two sub-samples as robustness checks (in one we retain only those who participate in both baseline and environmental uncertainty treatments, and in other one we limit it to baseline estimates only, when relevant). The solid horizontal line indicates zero, and the dashed horizontal line indicates the central estimates from Finkbeiner *et al*, [14]. Note the different y-axis scales between plots.

3.3. Assessing the effects of shocks on behavioral responses

A novel insight from our analysis is that information about environmental uncertainty alone (*i.e.*, the possibility that an environmental shock will significantly reduce future stock size) does not induce a behavioral response in fishers. When restricting the sample to observations that occur before any shocks, we find no significant treatment effects ($\hat{\beta}_1 = -0.031; p = 0.3$; Table 1B). This suggests that adaptation occurs only after fishers experience their first shock, which we corroborate with an analysis of dynamic effects.

Table 1: **Coefficient estimates for the effect of game round and environmental uncertainty on catch rate.** Panel A shows summary statistics associated with the validation results plotted in Fig 5. Panel B shows results for testing for the effect of information alone.

	Full	Both treatments	Baseline only
Panel A) Validation analysis			
Round	-0.009***	-0.008*	-0.010***
	(0.003)	(0.004)	(0.003)
Env. Uncertainty	-0.091***	-0.102***	
	(0.021)	(0.023)	
Num.Obs.	740	590	150
Panel B) Information only			
Round	-0.006**	-0.005	-0.010***
	(0.003)	(0.004)	(0.003)
Env. Uncertainty	-0.031	-0.032	
	(0.029)	(0.034)	
Num.Obs.	522	372	150

$*p < 0.1, **p < 0.05, ***p < 0.01$

Each column represents results for a different sample. Each panel represents a different test. Numbers in parentheses are Driscol-Kraay Standard errors. All specifications include fixed-effects by region.

We find that all coefficients leading to the impact are not significantly different from zero (Figure 6). Then, after the shock is realized, fishers reduce their catch rates by more than 0.11, on average, for at least three consecutive rounds ($p < 0.1$; See Figure 6 and Table B.1). Their catch rates remain lower than before the shock, though not significantly so for all five rounds (Figure 6). The coefficients on the dummy variables indicating observations that occur outside the 5-day window considered in the dynamic effects are also consistent, with no significant differences before ($\hat{\alpha_1} = 0.024; p = 0.54$), and significantly negative differences after ($\hat{\alpha_2} = -0.139; p < 0.1$; see Table B.1). The dynamic treatment effects are also robust to other linear regression specifications and to estimators specifically designed for staggered treatment adoption and repeated treatments (See Figure B.1).

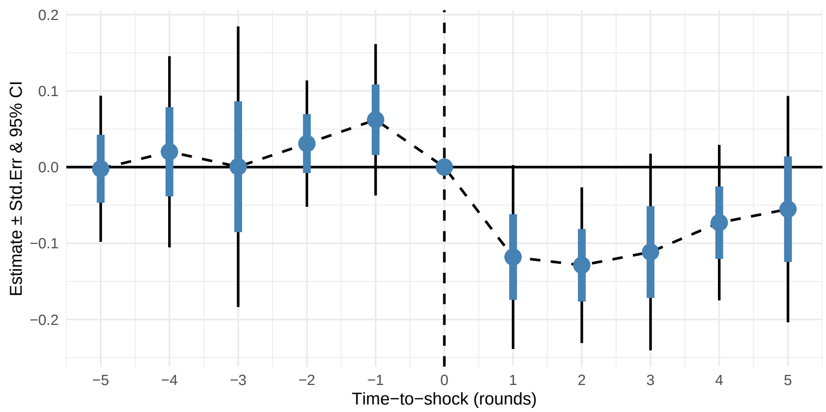

Figure 6: **Event-study plot for change in catch rate relative to time of the shock.** Points show coefficient estimates (relative to the round in which the shock was delivered), the blue portion of the error bars shows standard errors, and the black portion of the error bar shows 95% confidence intervals. Recall that the shock is delivered at the end of the round. The figure shows no significant changes in catch rates for the 5 rounds leading to the shock, and a significant decrease in catch rates (*i.e.*, adaptation) once a shock has been realized. The effect lasts for 2 ($p < 0.05$) rounds after the shock.

4. Discussion and Conclusions

Our objective was to explore the potential use of digital economic experiments as a way to scale-up the study of adaptation in small-scale fisheries. We asked whether we could recruit enough participants, and whether their responses could be compared with those reported by similar in-person experiments. We found that it is relatively easy and cheap (around $18 USD / participant) to recruit participants, and that their behavior is in general agreement with previously reported studies (although very few remained engaged through the game). Namely, both in person and digital experiments reveal a monotonic reduction in catch rates through time, and a further reduction of catch rates when faced with uncertainty of an environmental shock [14]. Importantly, we provide a new finding, where we show that information of environmental uncertainty alone is not enough to induce a behavioral change. Instead, fishers reduce their harvest only after they have actually experienced the shock. In addition, we find that the effect of adaptation is brief. Exit interviews with players conducted by Finkbeiner et al[14] had highlighted that previous experience with an environmental shock was a correlate of voluntary catch reduction in this previous experiment. Our digital experiment and analysis presented here supports this hypothesized effect, thereby providing an explanatory mechanism for variable adaptive responses across communities, and an expectation that adaptive responses may increase as the occurrence of extreme events escalate under climate change scenarios [27]. In the following lines we expand on each of these points, provide caveats related to our analysis and lessons learned, and provide concluding remarks.

4.1. Recruitment

The link between reading a media post and clicking on the button that deployed the game was the largest bottle-neck in the sample acquisition pipeline, suggesting the largest marginal gains can be made here. To overcome the challenge of the observed large drop between interaction with the platform and engagement through the game, future efforts could consider incentivizing potential users to engage with the game by offering a reward or other incentives [28, 29, 22]. We decided against it because fulfilling the reward is logistically difficult (fishers from anywhere in Mexico could play), and because we were explicitly interested in testing for the feasibility of digital experiments in its simplest form: a link to the game, and an invitation to play. Future efforts should balance the costs of incentivizing participation *versus* paying for promotion of social media posts or expanding the initial pool of potential surveyees. Alternatively, longer promotional campaigns and increased media activity and exposure may suffice to generate larger sample sizes. Formally assessing the feasibility and efficacy of these different approaches to increasing engagement is a critical next step before digital platforms can be broadly used for addressing research questions of adaptive responses to environmental uncertainty and other shocks.

4.2. Validity

Even with the limited sample size, we find general agreement with previous behavioral economic field experiments by Finkbeiner et al. [14], which suggests that digital economic experiments may provide a scalable solution to study adaptation in small-scale fisheries. Although we found similar results (monotonic reductions in catch rate through time and further reduction in the face of environmental uncertainty), our estimates of treatment effect (environmental uncertainty) indicate a larger reduction in catch rates than that reported for in-person experiments.

There are a few potential explanations for this. First, our sample size may limit our ability to retrieve the true parameter implying our estimates are biased. Second, our estimates are unbiased and the difference arises purely due to the game being played online, rather than in-person. These could be because people enjoy full anonymity in the digital games, or because the in-person games provide the opportunity for non-verbal cues and body language to still play a role. A third option is that the monetary incentives in the field could enhance the relative payoffs from immediate extractions in the game under the uncertainty of a sudden stock reduction. A final option is that fishers have had time to learn to adapt to climate change since the original experiments by Finkbeiner et al. [14](back in 2015), for example through the prolonged and extreme marine heat wave that has affected the region starting in 2014 and through 2016 [21]. Based on our result that direct experience with an environmental shock significantly affects behavior, we believe the most likely explanation is that most fishers have now been exposed to some of the adverse effects of climate change, and that they have internalized adaptation routes [30]. This is also consistent with previous research on strength of adaptive responses as it relates to historical exposure to climactic events [27].

4.3. Implications

Our results show that digital platforms hold great potential to scale up the study of adaptation in small-scale fisheries. This could provide decision makers, civil society organizations and academic researchers a relatively cheap, fast, and scalable solution to deploy experiments investigating adaptation to ongoing shocks, and test the outcomes of new policies before they are implemented. Further research should expand on our analysis, including testing for external validity and sampling representation.

We also found that, even when fishers were provided with information on the potential of a shock, they failed to adapt until the shock had been realized. This is concerning, given that many fishery managers, politicians, and environmental scientists often rely on "environmental outreach" or "communication" to share insights from the climate science community. Our results suggest that, to a large extent, fishers may ignore these messages until they experience the problem themselves. This finding may have implications beyond fishers, and raises an intriguing area of research about the role of individual experience in adaptation and behavioral modification. This also opens up the possibility to explore whether and how different ways of communicating the potential of a shock may induce a behavioral response. These games provide support to the argument that we need to pay attention to the cognitive biases and limitations that affect humans when making complex decisions[31] where, in our context, they must face the problem of cooperation with other fishers while solving the challenge of anticipating future shocks that can affect payoffs in the future. Moreover, the games themselves might be explored as tools for creating experiences with environmental change and uncertainty, and their potential use for awareness and engagement of key actors as well as the general public could be further investigated.

4.4. Limitations

We consider that the ShinyApps framework provides sufficient control over the development of the web-based platform that we used to deploy the games. The approach has been used in academia to build a large sample of solutions-oriented web-based apps, from evaluating community-based marine reserves [32] or simulating potential effects of subsidy reforms [33]. However, we recognize that the approach has some limitations, which may become increasingly relevant for other studies. Firstly, there is a certain barrier to entry in learning how to write the scripts that control the user interface and the back-end of the game. Fortunately, others have developed valuable guidelines and best-practices to inform the use of ShinyApps in academic research [34, 35], which provide useful insights to those interested in implementing this approach.

Another limitation is that, as currently implemented, the game does not allow for peer-to-peer connections where fishers may play against or in coordination with each other, instead of with the pre-programmed virtual fishers. This is an important point, as it is crucial that experiments replicate the social dynamics of decision-making that may arise in the real world. Although we note that the limitation could be bypassed by hosting the platform on private servers rather than on those provided by shinyapps.io services, which employ ephemeral connections to make computation more efficient and accessible. We further note that a way to work around both of these limitations is for research teams to engage with professional software developers, who have the knowledge and expertise required to build the right tool for modest cost. This is something that we are ourselves considering, now that we have confirmed the feasibility of the approach. We certainly hope others will follow.

Finally, we emphasize that our estimates of behavioral responses are derived from a total of 740 rounds played, which come from a small number of users who played both games (N = 11). We are confident in the general results about behavioral changes because these are robust to a series of other tests and specifications (See supplementary materials), and because they are in alignment with previous findings [14]. Nonetheless, recall that our main objective was to test for the feasibility of using digital technologies to deploy behavioral experiments, with the secondary objective of drawing inference on new processes (*i.e.*, that adaptation ensues only after experiencing a shock).

4.5. Conclusions

We conclude that digital economic experiments provide a feasible, cost-effective, and scalable alternative to study adaptation in small-scale fishers. We encourage other researchers to leverage digital technologies to perform large-scale deployments of digital economic experiments. Additionally, we find that information about uncertainty alone is not enough to induce a behavioral change in fishers: adaptation ensues once the threat has materialized.

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Appendix A. Supplementary text

Pseudo-code and mathematical representation of the game experiment

The timing of events is the following:

1. The user observes N_t, total stock size in round t
2. User i choses a catch level (0-5) for round t, given by: $h_{i,t}$. This is their choice variable, and what we will use as a response variable.
3. Bots are also pre-programmed to fish as a function of round and treatment status, so we must account for their catch. Total catch at time t is simply the sum of everyone's catch, given by:: $H_t = \sum_{1=1}^{5} h_{i,t}$
4. We can then calculate escapement at time t as: $E_t = N_t - H_t$.
5. The resource then groups according to the following equation of motion:

$$N_{t+1} = (1 + r)E_t\gamma_t(1 - \mu_t) \tag{A.1}$$

Where:

- r is the resource's intrinsic growth rate, with a constant value of $(r = 0.1)$
- If the player is playing the environmental uncertainty treatment, then: γ_t is the environmental variation parameter, drawn from a log-normal distribution such that:: γ_t $\text{lnorm}(1, 0.1)$

6. μ_t is the mortality rate under a shock at time t. It takes a value of 0 in the absence of a shock, or 0.5 otherwise.item The app shows the user the resulting population size $(N_t + 1)$, and we begin at point 1 again.

Appendix B. Supplementary figures and tables

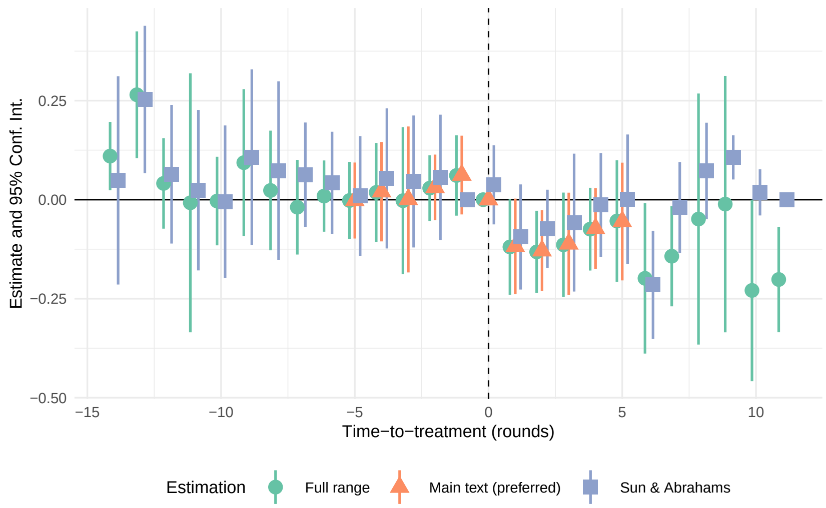

Figure B.1: **Alternative specifications and estimators applied to the event-study analysis.** The x-axis shows the number of rounds leading to and after the treatment. Points show coefficient estimates. Each color corresponds to a different estimation strategy. Our main-text results for dynamic effects (limited to ± 5 rounds) are similar to those estimated with data from all rounds and drop the pre- and post- dummy variables, and when we use the Sun & Abrahams [26] estimator for staggered treatment adoption.

Table B.1: **Coefficient estimates for event study**

	(1)	
	Est.	S.E.
pre	0.024	0.039
post	-0.140*	0.069
ttt = -5	-0.002	0.045
ttt = -4	0.020	0.059
ttt = -3	0.001	0.086
ttt = -2	0.031	0.039
ttt = -1	0.062	0.046
ttt = 1	-0.118*	0.056
ttt = 2	-0.129**	0.048
ttt = 3	-0.112*	0.060
ttt = 4	-0.073	0.048
ttt = 5	-0.055	0.069
Num.Obs.	520	

$*p < 0.1, **p < 0.05, ***p < 0.01$

ttt indicates 'time-to-treatment', with negative values ocurring before shock and positive values after shock.