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Experiments on partnership and decision making in a disaster environment

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ABSTRACT

The time of entry and the desired activity into a disaster area play an important role in leading to the optimal mix of partners for an agency operating in a disaster scenario. In this paper, based on current literature and interviews in disaster environments by the authors, we designed and executed six experiments. Each experiment is designed to measure a particular component of how agencies make partnership decisions in a disaster environment, with the goal of developing a model of how such decisions would affect operational efficacy. In each experiment, players made partnership and resource allocation decisions in a simulated disaster environment. A wide range of experimental data were gathered to understand how different information influenced decision-making. Each trial of the six experiments had random parameter values, and a logic component for how other agencies in the disaster environment acted with stochastic perturbation. Based on the results of each experiment, we developed a simple model that used the most significant drivers of participant performance. The significant factors in decision making during simulated disaster operations included: agency efficiency, past project investment, partner size, significance of impact on the population, and the amount of remaining need. The impact of this work is two-fold: 1) Identifying some of the underlying biases in human decision making when engaging in cooperative competition, or "coopetition," and 2) Providing simple decision-making models for understanding, simulating, and predicting agency behavior as part of a disaster response operation.

1. Introduction

The ever-increasing number of people and equipment involved in disaster relief operations has resulted in a significant increase in the complexity of problems in the domain of interagency partnerships. The number of potential relationships that agencies can choose from has exploded, making coordination of efforts much more complicated when developing an effective supply chain for emergency relief operations [2,11,21]. People and agencies will likely remain at the center of relief operations for the foreseeable future due to their versatility, making it extremely important to understand how to motivate, coordinate, and facilitate effective work [1].

This paper presents a series of six experiments to develop a flexible decision-making model for implementation in a disaster response simulation. The design of each experiment was based on a series of interviews that were conducted with agencies who were, or had been previously, active in a disaster operation. The interviews were conducted in Port-au-Prince, Haiti; Joplin, Missouri; and in New York and New Jersey along the Atlantic Coast. These interviews provided insights into how agency operations changed over time, and provided a range of parameters that could be used in simulation models. See Coles et al. [4] for detailed information about the interview approach and initial results.

Each of the six experiments were designed around specific trade-off decisions that agencies were observed to make during a relief operation. The goal of the study was to understand what typical range of human behavior might occur in a similar scenario by having a broad range of individuals make decisions in an experimental environment. From the results of each of the experiments, we constructed a model that could be used for simulating a broad range of agencies in a simulated environment. The summary and decision trade-off for each of the six experiments are listed below:

1. Receiving offers from other agencies to work together. Decision was to accept or reject the current offer of partnership, as the

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pool of potential partners shrunk.
2. Making offers to other agencies to work together. Decision was to make an offer to a partner to utilize resources without a partnership.
3. Resource allocation between different projects in a two-project environment. Decision was how to split resources at each time step between the projects.
4. Determine when to end a specific partnership. Decision was whether to continue or to terminate partnerships at each time step.
5. Determine when to end engagement in a whole aspect of relief (e.g., ending home construction). Decision was whether or not to stop investing in a set of projects, with the caveat that unlike Experiment 3, there was no re-investing in those projects.
6. Determine when to stop working in a disaster area. Decision was when to leave entirely and stop investing in the work in the current region, opting instead for an alternative region.

The rest of this paper is organized as follows: Section 2 provides background on the domain and the research approach; Section 3 summarizes the experimental design and method, including the participants, variables, and assumptions; Section 4 walks through the details and design of each of the experiments; Section 5 describes the experimental results; and Section 6 summarizes some of the key implications, opportunities, and future research directions to emerge from this work.

2. Background

The approach taken in this paper cuts across several different fields of practice including sociology, economics, simulation, and engineering. In this section, we highlight some of the literature that is pertinent to understanding the underpinnings of our approach, while recognizing that there is still significant opportunity for further exploring and integrating the different domains. Since the study of interagency partnerships in disaster relief work is relatively new, some of the work was developed in partnership with experts in the areas of economics and sociology [3,14,17,18]. These partners provided valuable feedback on the data collection techniques used for this work (e.g., interview structure and experimental design). This provided the necessary support to collect data and run experiments that provide new insight into how people make decisions, such as selecting partners and allocating scarce resources in uncertain environments, like disasters.

The set of experiments discussed here were developed using information collected in Haiti [4], information from the interviews with the agencies in EF-5 Tornado in New York/New Jersey [5], and current literature on experimental data collection [8,13]. Although a significant amount of data was collected from interviews with agencies involved in relief operations, due to the time constraints of a relief operation and the infrequency of disasters it is important to collect additional data using a controlled experimental environment.

Documented and published research where post-event/exercise analysis has generated reliable data that could be used to study disaster response is relatively rare [9]. One of the key challenges highlighted by Killian [12] is that it is extremely difficult to collect data in a disaster response environment, something that has been re-iterated and clearly evident in the body of speculative literature in the disaster domain. Kanno and Furuta [10] conduct questionnaire surveys and interviews of emergency responders, such as local government officials, experts, and police, to ultimately present an Emergency Response Systems (ERS). The focus was understanding the sufficiency, reliability, and resilience of an ERS. Kanno and Furuta [10] conclude that it is primarily “based on previous experience and tact,” that accounts for why responses among organizations and individuals are very different during disaster relief operations. This highlights the need to develop an understanding of, and model of, the range of actions that might be taken by different individuals and organizations. This paradigm puts the emphasis on understanding and providing the right support, rather than attempting to find the perfect top-down model of disaster relief coordination.

To ground new work around disaster relief and behavioral modeling, it is critical to highlight some of the work in communication and resilience, (e.g., Rogers et al. [19]) where Rogers examines how resilience experts could collaborate in order to improve disaster prevention, management, and mitigation practices. As the study of inter-personal and interagency communication within disaster relief increases, it is important to account for the changing landscape of participants. Coupet et al. [7] develop a network of capable local healthcare providers which allows Haitian nationals to be legitimate partners in relief operations, shifting away from a paradigm of aid recipients to partners.

In this work, we build on the communication and partner approach elements of disaster relief, focusing on building experiments and models to understand more generally how relationships impact outcomes. McCarthy et al. [16] study the risk communication in flood incident management, which provides valuable insight on how to build and analyze the results of the experiments presented here. Additionally, to put the experimental results in context, it is important to highlight Saeidian et al. [20] which consider the establishment of temporary relief centers in earthquake disaster relief. Finally, Marcelin et al. [15] study a spatial network optimization analysis of hurricane relief facility locations in post-disaster relief. This breadth of work provides the foundation for understanding how agencies locate, interact, behave, and leave over the course of a disaster relief operation.

3. Experimental methods

The participants included in this study consisted of students from the University at Buffalo (UB). Experiments were conducted over 8 sessions, and ranged between 4 and 15 participants per session. Study participants were not required to have prior experience with disaster relief operations, but information about the individuals participating in the experiment provided an additional point of reference for future work-performance comparisons and model tuning.

Prior to beginning the experiment, the research assistant conducting the session would read through an introduction of the experimental components and decision alternatives. Each participant was given information about a disaster relief operation in which he/she was participating, and asked to make decisions in six different experiments. The circumstances for each experiment were randomly generated and replicated for 20 trials. The stated objective of each experiment was to maximize the number of people assisted, and the participant's metric for success was whether or not the average people assisted across all trials was higher than the expected experimental outcomes if there was no intervention.

Participants were paid for their time at an hourly rate with performance incentives for helping more people than was “expected” based on their experimental parameters. Participants were asked to complete more trials than necessary, and the number of trials not used in the data analysis was calculated based on exit interviews with participants after they had completed all six experiments. This “warm up period” allowed participants to practice the experiment and gain a better understanding of the impact of each decision, without significantly extending the length of each data collection session.

3.1. Experiment variables

In each experiment participants were only asked to make a single type of decision (e.g., responding to a request, ending a partnership). Each experimental trial was auto-generated based on several variables derived from the results of the interviews. The upper and lower bounds for each variable was simplified to provide clear decision alternatives for participants.

3.1.1. Indices

Here we present the different indices that were used in the disaster experiment. The presentation of variables assumes a generic set of disaster indices rather than explicitly defining a set of A and B variables.

i=Index for an agency, where there are I agencies in the system. Let $i=0$ for the participant.
j=Index for agency partners.
t=Index for the time/decision period where there are T periods. In Experiments 3–6, participants were asked to make a decision for a certain number of time periods. In experimental models where the number of partnership slots was not taken into account, the number of decision epochs was used to control the length of the trial.
h=Index for type of aid needed: $\{1(\text{Type } A), 2(\text{Type } B)\} \in h$ where type A is the need that resulted from the disaster and type B is the need that is typical of a community. Here we also refer to them as short-term (type A) and long-term (type B) need.
o=Index for offer number in a given period where an agency receives a total of O offers.

3.1.2. System Variables

The information for a participant's agency and disaster environment was varied using the following parameters for each trial.

S_i=Agency Size: Each agency was given a size randomly distributed between 1 and 10; this was the amount of impact that could be achieved per partnership in Experiments 1 and 2. The primary reason this range was chosen was to limit the range of decision comparisons to simplify the participant experience. The agency size in the agent-base model can be generalized to any range using the base 1–10 scale for small to large. However, having a wide range of sizes of the agencies involved was important in order to capture the magnitude of potential differences in capabilities between organizations.

$PL_{i,t}$=Remaining Number of Partnership Slots:The number of partnership slots ranged from 1 to 15 in the different experiments. The reason for this was that in the interviews, over 95% of the agencies discussed information about less than 15 partners, and this scaled well to the decision-making environment where participants were asked to make decisions about partnerships individually. The maximum number of partner slots an agency could have in a particular experiment is indicated by $PL_{i,0}$.

E_i=Agency Efficiency: The efficiency of an agency ranged from 0 to 1, and was multiplied by the agency size to give a uniform range from 0 to the agency size: $(1 - S_i)$. To minimize the cognitive load on a participant, the agency impact was only provided in increments of 0.5.

$PS^{h,i,j,t}$=Partnership Investment: The size of partnerships in Experiment 4 ranged from 1 to 4, with investment in types A and B aid (h=1,2). Since some partnerships resulted in greater impacts than others, it was important to be able to clearly identify what decision maker preferences might be contributing to the longevity of a particular partnership. The concept of mixed investments was initially explored in Experiment 3 where the participant could choose to invest 0–4 resources in project type A or B. This concept was then extended in Experiment 4 where participants were able to choose when to end a particular partnership that had a mixture of potential resource impacts (e.g., invested more in project type A or B). Since the potential impact of investment in project types A vs. B changed over time, it was important to account for the difference in partnerships with different emphases. It should also be noted that $PS_{h,i,j,t} = PS_{h,j,i,t}$, and that $PS_{h,i,j,t} = 0$ if no partnership exists.

$G_{h,i,t}$=Total Agency Investment: The total number of resources invested in type h aid by agency i across all partnerships. We have $G_{h,i,t} = \sum_{j=1}^{I} PS_{h,i,j,t}$.

$Q_{i,t,o}$=Agency Offer: Size of agency i offer o in Period t. Over the course of a period, an agency received a wide range of partnership offers from other agencies. The size of previous offers helped to inform an agency of the possible partnerships in the disaster area.

R_i=Agency Alternative Project Impact: Each agency in the system had an alternative project efficiency that was scaled from 0 to 1. This helped a decision maker to decide whether or not to leave the disaster area for an alternative project.

N_t=Number of Agencies in the Region: The number of agencies in the region had a significant impact on the availability of partners in Experiments 1 and 2, and the rate at which the relief effort progressed in Experiments 3–6. It should be noted that the size $N_0=I$.

$H_{h,t}$=Quantity of Need: The amount of re-occurring need in the community was considered to be type B aid (h=2), and ranged in scope for each experiment from 0.1 to 2 times the total capability of the agencies in the region or $H_{2,0} = \sum_i^I S_i$. Similarly, the size of the disaster was indicated by the amount of type A aid needed ($H_{1,t}$). The initial amount of need was given by $H_{1,0}$, and was also calculated as a proportion of the base aid needed using a random multiplier between 0.1 and 15 times the total capacity of the agents in the system.

$W_{h,t}$=Impact per Resource: The impact (e.g., number of people helped) per resource was calculated as a function of the amount of need in the area and the amount of investment from all agencies, and was calculated for every period t. $W_{h,0}$ was assumed to be the maximum amount of impact possible per resource for each type of need h.

3.2. Assumptions

Some of the experimental parameters were kept constant across all experiments and have a correlated assumption. Here we address fixed model parameters and other assumptions behind the model.

- Rate of Change for Resource Investment: In the experiments where each agency was investing resources in type A or B aid (Experiments 3–6), the automated agencies in the experiment would alter their investment one resource at a time once the efficacy of one type aid was greater than the other (i.e., $W_{h,k} > Wb_{h',k}$), and would not alter the current investment structure if there was no difference in impact. Since not all real-world decision makers take such a slow (1 resource at a time) or simplistic approach to altering investment decisions, we incorporated an additional random component to highlight the dynamic components of the model called the Perturbation Factor.
- Perturbation Factor: To allow some agencies to shift resources faster than one per period, we incorporated a perturbation factor of 25% such that some percentage of agencies could shift

their resources more quickly from one project to another (e.g., all resources to type A if $Wa_k > Wb_k$). This provided an increased fluctuation in the efficacy of projects in type A and B, which aided in identifying participant preferences in the face of uncertain payoffs.

- Desperation Factor: The Desperation Ratio was calculated as the number of partner slots remaining divided by the number of agencies remaining in the region.
- Payoff Calculation for Aid: The impact per resource was calculated as shown in Eqs. (1) and (2) for type A and B need. It should be noted that the impact factor was scaled to the remaining amount of need to ensure agency projects were bounded by the current amount of need in the community. Eq. (1) is shown for type h aid for a generic case of agency i and is looped through all agencies in the system.

$$aggregatedImpactFraction_{h,i} = \frac{G_{h,i,t-1}}{H_{h,t-1}} - \frac{G_{h,i,t-1} aggregatedImpactFraction_{h,i-1}}{H_{h,t-1}} \tag{1}$$

$$W_{h,t} = \frac{aggregatedImpactFraction_{h,i} W_{h,0} \sum_{i=0}^{I} (G_{h,i,t})}{H_{h,t-1}} \tag{2}$$

- Replenishing Type B Need: Type B was assumed to be a type of long-term, re-occurring need in the region. By definition, type B need is the number of services provided to people during a period for an average period. Thus, in every period it is assumed that this need regenerates, independent of whether the prior level of type B need was reduced through agency efforts ($H_{h,t} = H_{h,0} - \sum_{i=0}^{I} (G_{h,i,t-1} H_{h,t-1})$).
- Constant Number of Agencies: In experiments 3–6, the number of agencies in the region during the time-frame of the disaster relief effort was kept constant to reduce the number of confounding variables (i.e., $N_t = N_{t-1}, \forall\, t \in T$).

4. Overview of the experiments

Each experiment provided a unique decision environment for the research participants. In this section we introduce each of the experiments and discuss the design and goals with supporting visuals. The experiments were built in Excel using Visual Basic for Applications®. Each trial of the six experiments had randomly generated parameters, and a logic component for how other agencies in the disaster environment acted.

In Experiments 1 and 2, the other agencies in the region were given a random set of parameters taken from the same range as the participant (e.g., agency size from 1 to 10, number of partner slots from 1 to 15). Each of the agencies also sought partners and accepted partnership offers from any agency that was bigger, but would also accept partners that were smaller based on a random variable and the "Desperation Ratio," as discussed in the previous section. In Experiments 3, 4, 5, and 6, the other agencies in the region were also given a random set of parameters taken from the same range as the participant (e.g., agency size from 1 to 4, number of partner slots from 1 to 15). The Appendix provides the screenshots as well as the explanations of the six experiments.

4.1. Experiment 1: receiving offers from other agencies

In this experiment, the participant was responsible for managing a disaster relief organization by making a series of decisions about with what other agencies in the disaster area would work be acceptable. Each partner ranged in size from 1 to 10 based on the number of people who would be assisted if the partnership was accepted. Participants were shown the screen and could use the information highlighted to decide how to help the most people. When the experiment ended, participants were shown a message giving the average number of people assisted per partnership slot, and reminded of the objective average across all trials (8 people/slot).

4.2. Experiment 2: making offers to other agencies

Similar to Experiment 1, participants were trying to find a set of partners to help people. However, in this experiment the participant made offers (instead of receiving offers) using a limited amount of resources equivalent to the number of offers the participant could make. The participant was told the number of people that could be assisted without a partnership and had to choose whether to spend the resources searching for a partner or select the default resource impact.

Since the participant was making offers to other agencies, offers could be rejected. If this happened, the participant was not able to recoup the lost investment. Additionally, the participant would only know the size of the possible partner if the offer was accepted.

The experiment ended when the participant ran out of resources (e.g., partnership slots) or chose to stop seeking partners. The projected impact was shown on the "Submit Trial" button if the participant was to stop seeking partnerships. When the experiment ended, a message was shown stating the objective for this experiment (4 people/resource), and the average number of people assisted by the participant during the previous trial.

4.3. Experiment 3: resource allocation

In this experiment, the participant was faced with two different projects (Project A and Project B) that had varying impacts over time, and was asked to split his/her resources between the two projects for multiple periods. After the participant made the decision of how to split the resources, he/she would be shown the impact from the period. This new information could then be used to inform any shifts in resource allocation for the next period. All other agencies in the disaster environment also made the same resource allocation decision for each period. The experiment ended when the participant ran out of decision periods. A message was then shown stating the objective for this experiment (35 people/resource) and the average number of people the participant assisted per resource in the previous trial.

4.4. Experiment 4: partnership length

This experiment built on Experiment 3 to determine how long the participant would stay invested in a particular partnership with mixed resource allocation. The participant was given a set of randomly generated partnerships that had a mixture of investments between Projects A and B. In each period, the participant was asked which partnerships should end and which should continue for another period.

Once the participant ended a partnership there was no way to reinvest in that partnership for this experiment. Instead, for each resource that was invested in the partnership, a fixed resource conversion rate was used (as highlighted in Fig. 6, part F) to calculate the number of people helped for all future periods. The experiment ended when the participant ran out of disaster periods or chose to end all partnerships. It is important to note that the number of possible decisions the participant was asked to make could have been as high as 15×15 (the number of the partners times the number of decision periods). This never occurred since participants ended at least some partnerships before all periods had passed, but this experiment typically took participants the longest amount of time. When the experiment ended, a message was shown stating the objective for this experiment (35 people/resource/period) and the average number of people the participant assisted per resource per period in the previous trial.

4.5. Experiment 5: ending projects

One of the most challenging problems in emergency management is choosing when to end a project entirely. This experiment built off of Experiment 3, where the participant had to choose how to balance resource investments between two projects. Here, the participant chose when to end a project entirely. The participant was shown an interface similar to Experiment 3, but had two decision alternatives: Continue investing in project A or switch entirely to project B.

It is important to note that when the participant chose to switch to project B, the experimental trial stopped immediately and the participant had no further control over the remaining periods (i.e., there was no way to continue to invest in project A once the participant had made the decision to switch). The model for resource investment and payoff in this experiment was the same as in Experiments 3 and 4, and the other agencies involved in the relief effort also behaved the same way. When the experiment ended, a message was shown stating the objective for this experiment (30 people/resource) and the average number of people the participant assisted per resource in the previous trial.

4.6. Experiment 6: time to cease operations

In this experiment, we built on the same idea explored in Experiment 5. When a disaster operation winds down, it is important to understand how and why agencies choose when to cease operations in the disaster area. In Experiment 6, the participant had to choose whether to stay in Region A or leave for Region B. Just as in Experiment 5, once the participant left the disaster area, he/she was not able to return.

The model for resource investment and payoff was identical to the model in Experiments 3, 4 and 5, except that type B payoff and need remained constant across all periods instead of dynamically updating. The other agencies involved in the relief effort also behaved the same way as they had during previous experiments. When the experiment ended, a message was shown stating the objective for this experiment (30 people/resource) and the average number of people the participant assisted per resource in the previous trial.

5. Experimental results

In this section, we review the experimental results. During the course of the study, 53 people participated in the experiment. Participants were given the option to skip any portion of the study that they did not want to answer.

5.1. Participant performance

Participant performance was assessed using two metrics: number of wins and average impact/resource. The number of wins across all the experiments was used in calculating how much to pay the individual, but this metric did not provide a great deal of information regarding performance since the win/loss assessment line was established with the objective of being achievable by the participant depending on effort, rather than providing a statistically valid performance metric.

The average number of people helped across all trials was estimated for each experiment as a metric to assess individual performance. Since the scenarios were randomly generated, each participant had a very similar opportunity to achieve the same level of aid across the experiments. In Figs. 1 and 2, some of the prior experience of individual participants is used to find if there was any clear correlation between performance and experience.

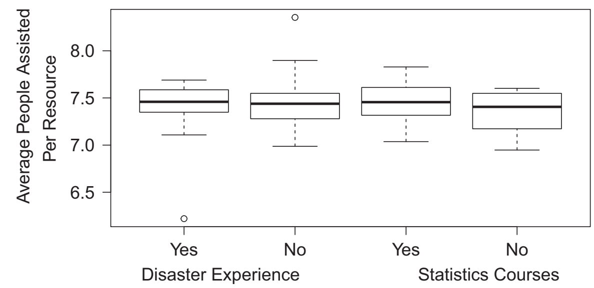

Fig. 1. Participant performance relative to disaster and statistics experience. It is interesting to note that having some disaster experience, or previous instruction in statistics, appeared to have no bearing on individual performance in the experiments.

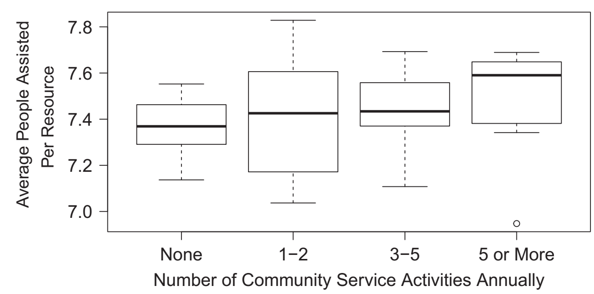

Fig. 2. Participant performance relative to frequency of community service. The average number of people assisted per resource across all experiments when participants were grouped by the frequency of community service.

As seen in Fig. 1, participants with more experience in disaster operations and those with greater familiarity with statistics did not perform significantly better than those without. This is important because the lack of significant difference provides a good indicator that the experiments captured the decision-making process independent of personal experience. As a result, we could safely use the results of the experimental decisions to provide a baseline for simulated decision behavior without concerns about bias due to previous experience or specific expertize.

Fig. 2 suggests a (weakly) positive correlation between community service and participant performance, recognizing some high level of variance in the data.

5.2. Learning curve and warm-up period

A one-sided confidence interval was used to estimate the appropriate number of trials for a warm up period with the following variables: $\bar{x}$) the sample mean from the *upper bounds* of participant estimates was 4.13; n) the number of participants that gave estimates was 45; and S_x) the sample variance was 2.45. The max z value where the true mean could be less that 5 trials was 1.36, which gave us a confidence of 91%, meaning that the worst case for a particular experiment is that 91% of the data used for analysis was generated when the participant fully understood the experiment.

5.3. Decision modeling

The decision models presented here were developed in R® using Multiple Linear Regression (MLR). This provided a simple set of decision rules that could be easily implemented in simulation or practice. Each of the decision models presented here were built using a portion (two-thirds) of the available data to generate a linear decision model. The model was then tested with the remaining third of the data to validate the predictive power of the model.

All parameters considered for the MLR analysis were normalized or scaled to make sure that the concept was transferable to a generic disaster context beyond the experimental environment. For example, we calculated the agency efficiency as a percentage of the maximum possible return instead of the experimental impact value. Each experiment was tested using a broad range of analysis components, but only factors that had a significant p-value are shown here. In order to account for as much error as possible, all variables that had p-values of 0.2 or smaller were kept. Since the majority of the decisions predicted here are binary (except for Experiment 3), the linear model output was converted into a binary result by rounding.

It is important to note that some of the factors are repeated between the different decision sets; however, in order to simplify the discussion of the different variables, the information is repeated and explained in the context of each experiment. Additionally, the variables discussed in Section 3.1 are used here to explain the different components of the decision model.

The enumerated components of each decision model are treated as variables in the following format: x_{e,d_e} where e=the decision model number (1–6), and d_e=is a decision metric for decision model e. Each model has a different number of components, such that d_e ranges from 1 to D_e. It is important to note that the coefficients for the model are denoted c_{e,d_e} with the initial constant as c_{0,d_e}. This allows the equations presented for the decision-making process to be calculated as shown in Eq. (3).

$$D_e = c_{0,d_e} + \sum_{d_e=1}^{D_e} (c_{e,d_e} x_{e,d_e}). \tag{3}$$

5.4. Results for experiment 1: receiving offers from other agencies

The decision model from Experiment 1 shows when an offer of partnership should be accepted or rejected. There were 11 different factors that had sufficiently significant p values to be included in our decision model. The weights for each factor are shown in Eq. (4).

$$D_1 = 0.32 - 0.097x_{1,1} - 0.453x_{1,2} - 0.268x_{1,3} - 0.187x_{1,4} - 0.118x_{1,5} - 0.054x_{1,6} + 2.058x_{1,7} - 0.033x_{1,8} + 0.06x_{1,9} \tag{4}$$

The model was trained on a dataset with 7100 data points, and tested on a separate set of about 3500 data points. The model accurately predicted the participant's decision 89% of the time.

- Agency Efficiency $x_{1,1}$ ($p < 0.001$): This agency parameter was calculated as the percent efficiency an agency had when working on a project without a tactical partner (E_i). This was generated from a uniform distribution with the following range [0, 1]. The negative value of $c_{1,1}$ means that the more efficient the decision maker's agency, the less likely a decision maker was to accept a partnership .
- Percentage of Partner Slots used $x_{1,2}(p < 0.001)$: Calculated as

  $$\frac{PL_{i,t}}{PL_{i,0}}.$$

  The negative value of $c_{1,2}$ means that the more partnership slots a decision maker had remaining, the less likely they were to accept a partnership. This was likely the result of a decision maker being more hesitant to accept an offer early in the search process unless it was excellent. This result should be interpreted in combination with variable $x_{1,4}$.
- Log of Offer Ratio $x_{1,3}(p < 0.001)$: The log of the offer ratio was calculated as

  $$\ln\left(\frac{\sum_{h=1}^{2}\left(PS_{h,i,j,t-1}\right)}{E_i S_i}\right).$$

  The negative value of $c_{1,3}$ means that a partnership was more likely to be accepted if it was closer in value to the potential impact without a partnership. This is a counter-intuitive result which should be explored in future research.
- Log of Partner Slots used $x_{1,4}(p < 0.001)$: Calculated as

  $$\ln\left(1 - \frac{PL_{i,t}}{PL_{i,0}}\right).$$

  The negative value of $c_{1,4}$ indicates that if a decision maker had used more partner slots he/she was less likely to accept an offer at a logarithmic rate. As a result, a decision maker with more partner slots would be slower to accept late offers than a decision maker with fewer slots.
- Log of Number of Offers $x_{1,5}(p < 0.001)$: Calculated as ln(Number of Offers). The negative value of $c_{1,5}$ indicates that the more offers a decision maker had received, the less likely he/she was to accept an offer.
- Difference between Offer Size and Agency Impact Scaled by Agency Impact $x_{1,6}(p < 0.001)$: Calculated as

  $$\frac{E_i S_i - \text{Offer Size}}{E_i S_i}.$$

  The negative value of $c_{1,6}$ indicates that a decision maker was more likely accept the partnership if the offer impact was greater than the agency impact.
- Normalized Offer Impact $x_{1,7}(p < 0.001)$: Calculated as

  $$\frac{\sum_{h=1}^{2}\left(PS_{h,i,j,t-1}\right)}{S_i}.$$

  The positive value of $c_{1,7}$ indicates that the bigger the offer impact, the more likely a decision maker was to accept the partnership.
- Scaled Moving Average of Avg. Partnership Returns $x_{1,8}(p = 0.008)$: Calculated as

  $$\frac{\dfrac{\sum_{h=1}^{2}\left(\sum_{j=1}^{I}\left(PS_{h,i,j,t-1}\right)\right)}{PL_{i,0} - PLi,\, t}}{E_i S_i}.$$

  The negative value of $c_{1,8}$ indicates that the higher the variability of current partnerships, the less likely a decision maker was to accept an offer.
- Scaled Moving Standard Deviation of Partnership Offers $x_{1,9}(p < 0.001)$: Calculated as

  $$\frac{StDev_o\left(Q_{i,t,o}\right)}{E_i S_i}.$$

  The positive value of $c_{1,9}$ indicates that the higher the variability of the offers received, the more likely a decision maker was to accept an offer.

5.5. Results for experiment 2: making offers to other agencies

The decision model in Experiment 2 was designed to find when an individual would pursue a partnership and invest resources without a guaranteed payoff. Four variables were found to have significant p values in our analysis, given Eq. (5).

$$D_2 = 0.798 + 0.256x_{2,1} + 0.103x_{2,2} - 0.111x_{2,3} - 0.053x_{2,4} \quad (5)$$

The model was trained on a dataset with 2500 data points and tested on a separate set of about 1250 data points. The model accurately predicted the participant's decision 90% of the time, but tended to be biased towards predicting that a participant would choose to keep looking for partners when tested at a break point of 0.5. This break point was explored further in Coles et al. [6] to see how it performed under experimental conditions.

- Difference Between Agency Potential and Agency Impact Scaled by Agency Potential $x_{2,1}(p = 0.002)$: Calculated as

  $\frac{S_i - E_i S_i}{E_i S_i}$.

  The positive value of $c_{2,1}$ indicates that the less efficient an agency was alone, the more likely a decision maker was to seek a partner.
- Average Partnership Returns Scaled by Agency Impact $x_{2,2}(p = 0.073)$: Calculated as

  $$\frac{E_i S_i - \frac{\sum_{h=1}^{2}\left(\sum_{j=1} I\left(PS_{h,i,j,t-1}\right)\right)}{PL_{i,0} - PLi,\ t}}{E_i S_i}.$$

  The positive value of $c_{2,2}$ indicates that the lower the average impact of current partnerships, the more likely a decision maker was to seek a new partner.
- Standard Deviation of Average Partnership Returns Scaled by Agency Impact $x_{2,3}(p = 0.024)$: Calculated as

  $$\frac{E_i S_i - \frac{\sum_{h=1}^{2}\left(\sum_{j=1} I\left(PS_{h,i,j,t-1}\right)\right)}{PL_{i,0} - PLi,\ t} - StDev_t\left(Avg_j\left(\sum_{h=1}^{2}\left(PS_{h,i,j,t-1}W_{h,t-1}\right)\right)\right)}{E_i S_i}.$$

  The negative value of $c_{2,3}$ indicates that if the standard deviation plus the current average of partnerships was greater than a decision maker's impact alone, the more likely he/she would be to make an offer. This is especially insightful in light of variable $x_{2,2}$; the combined result is that if the average impact of current partnerships was low, but if a decision maker had experienced some success with previous offers, then he/she was more likely to make future offers.
- Normalized Result of Attempted Partnership $x_{2,4}(p < 0.001)$: Calculated as

  $\frac{Q_{i,t,O}}{PL_{i,0}}$.

  The negative value of $c_{2,4}$ indicates that the fewer partnership slots a decision maker had, the less likely he/she was to make an offer if a previous offer was successful.

5.6. Results for experiment 3: resource allocation

This experiment looked at shifting resources between two different projects. It is important to note that in Eq. (6), a positive value indicates a shift towards type A aid and a negative value indicates a shift towards type B. The function returns 0 if the agent does not wish to shift any resources.

$$\begin{aligned} D_3 = &-0.441 + 0.445x_{3,1} - 0.106x_{3,2} + 0.767x_{3,3} + 0.112x_{3,4} \\ &- 0.003x_{3,5} + 0.003x_{3,6} - 0.152x_{3,7} - 0.003x_{3,8} + 0.084x_{3,9} \\ &+ 0.209x_{3,10} - 0.029x_{3,11} + 0.05x_{3,12} \end{aligned} \quad (6)$$

The model was trained on a dataset with 3650 data points, and tested on a separate set of about 1800 data points. Since the predicted variables were continuous, to validate this equation we used a confidence interval to test the difference between the predicted and the actual resources shifts. For 1800 data points, we found the difference to be normally distributed with an experimental mean of -0.018 and standard deviation of 0.202. Experimentally, this resulted in a prediction of shifting behavior within 10% of actual behavior in 73% of the cases observed, and within 20% for 84% of the cases observed. It is important to note that this is a relatively good degree of accuracy since this metric is used for shifting integers in a small set (e.g., agencies interviewed typically had less than 5 project focuses which means that an accuracy within 20% would be sufficient for the vast majority of agencies).

- Previous Period Percentage of Investment in A $x_{3,1}$ $(p < 0.001)$: Calculated as

  $$\sum_{j=1}^{I}\left(\frac{PS_{1,i,j,t-1}}{PS_{1,i,j,t-1} + PS_{2,i,j,t-1}}\right).$$

  The positive value of $c_{3,1}$ indicates that the more heavily invested in one type of aid a decision maker was, the more likely they were to continue to invest in that type of aid.
- Normalized Average A Impact $x_{3,2}(p = 0.077)$: Calculated as

  $\frac{Avg_t\left(H_{1,t}\right)}{W_{1,0}}$.

  The negative value of $c_{3,2}$ indicates that the higher the average impact of type A investment in previous periods, the more likely a decision maker was to consider shifting resources towards type B. It is important to note that this is counter-intuitive, but indicates that a decision maker might account for potential overcommitment by other agencies. This trend is similar to that highlighted by variable $x_{3,3}$.
- Normalized Average B Impact $x_{3,3}(p < 0.001)$: Calculated as

  $\frac{Avg_t\left(H_{2,t}\right)}{W_{2,0}}$.

  The positive value of $c_{3,3}$ indicates the same result as $x_{3,2}$: a decision maker was wary of a consistently high impact for a particular type of aid.
- Normalized Standard Deviation Impact A $x_{3,4}(p = 0.052)$: Calculated as

  $\frac{StDev_t\left(W_{1,t}\right)}{W_{1,0}}$.

  The positive value of $c_{3,4}$ indicates that the higher the variability of a type of aid, the more likely a decision maker was to invest resources in it. This is counter-intuitive, and could demonstrate a bias towards risk-seeking behavior in the participant population.
- Ratio of Original Type A to Type B Need $x_{3,5}(p < 0.001)$: Calculated as

  $\frac{H_{1,0}}{H_{2,0}}$.

  The negative value of $c_{3,5}$ indicates that the higher the difference in impact between two types of aid, the more likely a decision maker was to switch to the smaller aid type.

- Remaining Need Factor for Type B $x_{3,6}(p = 0.065)$: Calculated as

  $$\frac{H_{2,t}}{\sum_{i=0}^{I}\left(S_i W_{1,0}\right)}.$$

  Similar to the meaning of the coefficient $c_{3,5}$, the positive value of $c_{3,6}$ indicates that a decision maker was likely to switch to the type of aid that had a smaller total amount of need, potentially to avoid competition with other agencies.
- Ratio of Remaining Type A Need $x_{3,7}(p < 0.001)$: Calculated as

  $$\frac{H_{1,t}}{H_{1,0}}.$$

  The negative value of $c_{3,7}$ indicates the same trend as discussed for variables $x_{3,5}$ and $x_{3,6}$.
- Ratio of Remaining Type B Need $x_{3,8}(p = 0.027)$: Calculated as

  $$\frac{H_{2,t}}{H_{2,0}}.$$

  The negative value of $c_{3,8}$ goes against the general trend noticed for the three previous variables (tendency to shift to smaller projects). However it is important to note that type B aid was regenerating during the experiment, and the greater the accumulated need for type B, the more likely a decision maker was to switch to type B.
- Ratio of A to B Impact in Previous Period $x_{3,9}(p < 0.001)$: Calculated as

  $$\frac{W_{1,t-1}/W_{1,0}}{W_{2,t-1}/W_{2,0}}.$$

  The positive value of $c_{3,9}$ provides the intuitive result that a decision maker was more likely to move toward the type of aid that yielded a greater payoff.
- Normalized A Impact $x_{3,10}(p = 0.003)$: Calculated as

  $$\frac{W_{1,t-1}}{W_{1,0}}.$$

  The positive value of $c_{3,10}$ should be considered in contrast to $x_{3,2}$. The combination of the two gives the following result: overall, a decision maker was tempted to invest in the type of aid that had been undervalued in previous periods. However, the potential impact from the period immediately prior could still tempt a decision maker to switch.
- Normalized B Impact $x_{3,11}(p < 0.001)$: Calculated as

  $$\frac{W_{2,t-1}}{W_{2,0}}.$$

  When contrasted with the value of $c_{3,3}$, the negative value of $c_{3,11}$ gives the same insight as discussed for variable $x_{3,10}$.
- Log of Ratio of Remaining Type B Need $x_{3,12}(p < 0.001)$: Calculated as

  $$\ln\left(\frac{H_{2,t}}{H_{2,0}}\right).$$

  The positive value of $c_{3,12}$ indicates that a decision maker was hesitant to shift resources to type B, even when the amount of type B need was accumulating. This is consistent with the previous hesitation to commit to investing in the type of aid that had more accumulated need.

5.7. Results for experiment 4: partnership length

Experiment 4 was designed to find out when an agency would end partnerships in a disaster environment. Eq. (7) shows the equation developed from the MLR analysis to find when a participant chose to keep or to end a partnership. If $D_4 > 0.5$ then the participant chose to keep the partner, otherwise, the partnership was ended.

$$\begin{aligned} D_4 = {} & 0.535 + 0.033x_{4,1} - 0.004x_{4,2} + 0.339x_{4,3} + 0.002x_{4,4} \\ & + 0.689x_{4,5} + 0.003x_{4,6} - 0.009x_{4,7} - 0.003x_{4,8} - 0.061x_{4,9} \\ & + 0.017x_{4,10} - 0.114x_{4,11} + 0.234x_{4,12} - 0.134x_{4,13} \\ & + 0.033x_{4,14} + 0.018x_{4,15} - 0.011x_{4,16} - 0.055x_{4,17} \end{aligned} \tag{7}$$

The model was trained on a dataset with 17,500 data points and tested on a separate set of about 8800 data points. The model accurately predicted the participant's decision 92% of the time.

- Normalized Partnership Size $x_{4,1}(p < 0.001)$: Calculated as

  $$\frac{\sum_{h=1}^{2}\left(PS_{h,i,j,t-1}\right)}{S_i}.$$

  The positive value of $c_{4,1}$ indicates that the higher the percentage of resources that was used in a partnership, the more likely a decision maker was to keep it.
- Ratio of Original Type A to Type B Need $x_{4,2}(p = 0.033)$: Calculated as

  $$\frac{H_{1,0}}{H_{2,0}}.$$

  The negative value of $c_{4,2}$ indicates that the bigger the difference between type A and type B need, the more likely a decision maker was to keep a partnership.
- Percentage of Partnership Slots that are Filled $x_{4,3}(p < 0.001)$: Calculated as

  $$\frac{SL_{i,0} - SLi,\, t}{SL_{i,0}}.$$

  The positive value of $c_{4,3}$ indicates that the more partnership slots a decision maker had filled, the more likely he/she was to keep partnerships. This is an interesting insight which may demonstrate a trend towards keeping as many partnerships as possible, but once a decision maker began to end partnerships, he/she was more likely to end additional partnerships.
- Positive Normalized Partnership vs. Agency Impact $x_{4,4}(p = 0.053)$: Calculated as

  $$\mathrm{Max}\left(0,\ \frac{\sum_{h=1}^{2}\left(PS_{h,i,j,t-1}W_{h,t-1}\right) - E_i S_i}{E_i S_i}\right).$$

  The positive value of $c_{4,4}$ provides the obvious result that if a partnership has had more impact with a partner than without, the more likely a decision maker was to keep the partnership.
- Negative Normalized Partnership vs. Agency Impact $x_{4,5}(p < 0.001)$: Calculated as

  $$\mathrm{Min}\left(0,\ \frac{\sum_{h=1}^{2}\left(PS_{h,i,j,t-1}W_{h,t-1}\right) - E_i S_i}{E_i S_i}\right)$$

  for a particular partner j. The positive value of $c_{4,5}$ is consistent with the result discussed for variable $x_{4,4}$.
- Remaining Need Factor for Type A Aid $x_{4,6}(p < 0.001)$: Calculated as

  $$\frac{H_{1,t}}{\sum_{i=0}^{I}\left(S_i W_{1,0}\right)}.$$

The positive value of $c_{4,6}$ indicates that the greater the ratio of need to current investment, the more likely a decision maker was to keep all partnerships.

- Remaining Need Factor for Type B $x_{4,7}(p < 0.001)$: Calculated as

$$\frac{H_{2,t}}{\sum_{i=0}^{I}\left(S_i W_{1,0}\right)}.$$

The negative value of $c_{4,7}$ is consistent with the result for variable $x_{4,6}$.

- Ratio of Remaining Type A to Type B Need Factors $x_{4,8}(p < 0.001)$: Calculated as

$$\frac{H_{1,t}}{H_{2,t}}.$$

The negative value of $c_{4,8}$ indicates that the bigger the difference between type A and B aid, the less likely a decision maker was to keep a partnership.

- Ratio of Remaining Type A Need $x_{4,9}(p < 0.001)$: Calculated as

$$\frac{H_{1,t}}{H_{1,0}}.$$

The negative value of $c_{4,9}$ provides the insight that the more type A need, the less likely a decision maker was to keep a partnership. This result is likely due to the experimental design which gave agencies a random set of partners at the beginning of the disaster. Thus, a decision maker chose to end all inefficient partnerships as quickly as possible.

- Ratio of Remaining Type B Need $x_{4,10}(p < 0.001)$: Calculated as

$$\frac{H_{2,t}}{H_{2,0}}.$$

The positive value of $c_{4,10}$ complements the result for variable $x_{4,9}$, and indicates that the higher the amount of type B need the more likely a decision maker was to keep all current partnerships. Similar to the previous discussion, the fact that this coefficient is positive is also likely due to the fact that, in the experimental model, over time the partnerships that had been less efficient were ended, and only partnerships which had greater investment in type B need remained. This result is consistent with the literature which indicates that disaster partnerships are more stable as long-term projects become more important (i.e., long-term projects result in long-term partnerships).

- Ratio of A to B Impact in Previous Period $x_{4,11}(p < 0.001)$: Calculated as

$$\frac{W_{1,t-1}/W_{1,0}}{W_{2,t-1}/W_{2,0}}.$$

The negative value of $c_{4,11}$ indicates that the bigger the impact of type A relative to type B, the less likely a decision maker was to keep a partnership. The interaction of types A and B's impacts is unclear from this variable, so it is further explored for variables $x_{4,12}$ and $x_{4,13}$.

- Normalized A Impact $x_{4,12}(p < 0.001)$: Calculated as

$$\frac{W_{1,t-1}}{W_{1,0}}.$$

The positive value of $c_{4,12}$ indicates that the higher the impact achieved per resource for type A in the previous period, the more likely a decision maker was to keep a partnership. This information would not be insightful alone, but is when compared to variable $x_{4,13}$.

- Normalized B Impact $x_{4,13}(p = 0.004)$: Calculated as

$$\frac{W_{2,t-1}}{W_{2,0}}.$$

The negative value of $c_{4,13}$ indicates that the higher impact of type B need in the previous period, the less likely an agency is to keep a partnership. This information, combined with the discussion of variable $x_{4,12}$, indicates that a decision maker is more likely to keep partnerships with a high percentage of investment in type A for as long as possible before investing in partnerships that are focused on type B need.

- Log of Ratio of Original Type A to Type B Need $x_{4,14}(p < 0.001)$: Calculated as

$$\ln\left(\frac{H_{1,0}}{H_{2,0}}\right).$$

The positive value of $c_{4,14}$ indicates that the bigger the disaster event, the more likely a decision maker was to keep partnerships.

- Log of Ratio of Remaining Type A Need $x_{4,15}(p < 0.001)$: Calculated as

$$\ln\left(\frac{H_{1,t}}{H_{1,0}}\right).$$

The positive value of $c_{4,15}$ reinforces the result of variable $x_{4,14}$.

- Log of Ratio of Remaining Type B Need $x_{4,16}(p = 0.082)$: Calculated as

$$\ln\left(\frac{H_{2,t}}{H_{2,0}}\right).$$

The negative value of $c_{4,16}$ indicates that a decision maker was more likely to end current partnerships as the amount of need of type B increased. This is consistent with the earlier result of ending partnerships that were focused on type A aid over time and switching to partnerships that focused on type B need.

- Log of Ratio of A to B Impact in Previous Period $x_{4,17}(p < 0.001)$: Calculated as

$$\ln\left(\frac{W_{1,t-1}/W_{1,0}}{W_{2,t-1}/W_{2,0}}\right).$$

The negative value of $c_{4,17}$ indicates a similar result as discussed for variable $x_{4,11}$.

It was discovered that the behavior of participants was highly dependent on the interaction of the two disasters; this made it extremely difficult to have a consistent decision making model for when to end partnerships based on the (7). As a result, the results from Experiment 4 were not used in developing a future simulation model. Experiment 5 was used to construct a decision model for when an agency ended a partnership.

5.8. Results for experiment 5: ending project

The decision model from Experiment 5 was developed as a simplified companion to Experiment 4. Experiment 4 was initially designed to provide a model for how partnerships were ended, and Experiment 5 was built to be a future extension to the model proposed in Coles et al. [6] to understand how an agency might respond to multiple disaster events. The decision maker was given two choices: to continue working on project A or to switch entirely to project B. The results of the experiment were encoded in the linear decision model shown in Eq. (8). It is important to note that if a participant stayed in the disaster area, the dependent variable was 1, and if he/she chose to leave, the result was 0.

$$D_5 = 0.486 - 0.061x_{5,1} - 0.004x_{5,2} - 0.004x_{5,3} - 0.001x_{5,4} + 0.010x_{5,5} + 0.016x_{5,6} - 0.015x_{5,7} - 0.198x_{5,8} + 0.773x_{5,9} - 0.633x_{5,10} + 0.254x_{5,11} + 0.221x_{5,12} - 0.123x_{5,13} + 0.137x_{5,14} \quad (8)$$

The model was trained on a dataset with 3500 data points, and tested on a separate set of about 1700 data points. The model accurately predicted the participant's decision 90% of the time. The discussion below will discuss the decisions that were made by participants in the experiment using terminology consistent with the other experiments. We will follow with a discussion of how the decision model from this experiment could be used to decide when to end a partnership.

- Log of Decision Periods Passed $x_{5,1}(p < 0.001)$: Calculated as: $\ln(t)$. The negative value of $c_{5,1}$ indicates that the longer a decision maker had been involved in a response, the more likely he/she was to switch to a different disaster effort. This could be the result of an expected reduction in agency impact in future periods since the amount of one type of need typically reduces over time.
- Ratio of Original Type A to Type B Need $x_{5,2}(p = 0.003)$: Calculated as $\frac{H_{1,0}}{H_{2,0}}$. The negative value of $c_{5,2}$ indicates that the larger the original difference in need between type A and B need, the more likely a decision maker was to switch to the new effort.
- Ratio of Remaining Type A to Type B Need $x_{5,3}(p = 0.002)$: Calculated as $\frac{H_{1,t}}{H_{2,t}}$. The negative value of $c_{5,3}$ is the interaction effect of variables $x_{5,4}$ and $x_{5,5}$.
- Remaining Need Factor for Type A Aid $x_{5,4}(p = 0.061)$: Calculated as $\frac{H_{1,t}}{\sum_{i=0}^{I}\left(S_i W_{1,0}\right)}$. The negative value of $c_{5,4}$ indicates that a decision maker was hesitant to leave the current region even if there was a large number of other agencies assisting in the disaster.
- Remaining Need Factor for Type B $x_{5,5}(p = 0.001)$: Calculated as $\frac{H_{2,t}}{\sum_{i=0}^{I}\left(S_i W_{1,0}\right)}$. The positive value of $c_{5,5}$ is consistent with the result found for $x_{5,4}$.
- Ratio of Remaining Type A Need $x_{5,6}(p = 0.010)$: Calculated as $\frac{H_{1,t}}{H_{1,0}}$. The positive value of $c_{5,6}$ means that the higher the remaining amount of need in the current disaster, the more likely a decision maker was to stay. This is a counter-point to the discussion of $x_{5,4}$.
- Ratio of Remaining Type B Need $x_{5,7}(p = 0.004)$: Calculated as $\frac{H_{2,t}}{H_{2,0}}$. The negative value of $c_{5,7}$ indicates that the higher the amount of type B need, the more likely a decision maker was to switch to the new effort. This should be considered in light of the discussion for $x_{5,4}$, $x_{5,5}$, and $x_{5,6}$.
- Ratio of A to B Impact in Previous Period $x_{5,8}(p = 0.036)$: Calculated as $\frac{W_{1,t-1}/W_{1,0}}{W_{2,t-1}/W_{2,0}}$. The negative value of $c_{5,8}$ indicates that the higher the impact factor for disaster B, the more likely a decision maker was to switch to the new effort.
- Normalized A Impact $x_{5,9}(p < 0.001)$: Calculated as $\frac{W_{1,t-1}}{W_{1,0}}$. The positive value of $c_{5,9}$ logically indicates that the larger the overall impact of type A need, the more likely a decision maker was to stay.
- Normalized B Impact $x_{5,10}(p < 0.001)$: Calculated as $\frac{W_{2,t-1}}{W_{2,0}}$. The negative value of $c_{5,10}$, when analyzed in parallel to variable $x_{5,11}$, indicates that a single high-impact period for disaster type B was insufficient for a decision maker to switch; rather, a consistently positive impact had to be observed as indicated by the positive coefficient $c_{5,11}$.
- Normalized Average B Impact $x_{5,11}(p = 0.124)$: Calculated as $\frac{Avg_t\left(W_{2,t}\right)}{W_{2,0}}$. See the discussion for $x_{5,10}$.
- Normalized Average+Standard Deviation Impact A $x_{5,12}(p = 0.060)$: Calculated as $\frac{Avg_t\left(W_{1,t}\right) + StDev_t\left(W_{1,t}\right)}{W_{1,0}}$. The meaning of the positive value for $c_{5,12}$ is consistent with $x_{5,9}$.
- Normalized Average+Standard Deviation Impact B $x_{5,13}(p = 0.38)$: Calculated as $\frac{Avg_t\left(W_{2,t}\right) + StDev_t\left(W_{2,t}\right)}{W_{2,0}}$. The negative value of $c_{5,13}$ is consistent with the results for $x_{5,10}$ and $x_{5,11}$.
- Log of Ratio of Original Type A to Type B Need $x_{5,14}(p < 0.001)$: Calculated as $\ln\left(\frac{H_{1,0}}{H_{2,0}}\right)$. The positive value of $c_{5,14}$ indicates that the higher the original amount of type A need, the less likely a decision maker was to switch projects.

In the descriptions above, a participant's behavior is described from the perspective of choosing investment option A or B. Here we list the conversions necessary to utilize this model in a different decision-making context, where keeping the partnership is option A and ending the partnership is option B.

- Decision Periods Passed: The length of the partnership.
- Original Type A Need: Number of resources that could be

invested in a partnership at the beginning of the simulation.

- Original Type B Need: Number of resources that could be invested in a partnership at the beginning of the simulation.
- Current Type A Need: Number of resources actually invested in a partnership.
- Current Type B Need: Number of resources that would be available for a new partnership if the current partnership was ended.
- Current Type A Need Factor: Original Type A Need divided by Current Type A Need.
- Current Type B Need Factor: Original Type B Need divided by Current Type B Need.
- Current Type B Need Factor: Original Type B Need divided by Current Type B Need.
- Impact of Type A: Calculated using the partnership projects and resources.
- Impact of Type A: Calculated using the current agency project mix and resources projected to be available for a new partnership.

5.9. Results for experiment 6: time to cease operations

Experiment 6 explored the situation that would be required for an agency to leave the disaster environment. It is important to note that the region that was impacted by the disaster (Region A) is compared to a hypothetical alternative region (Region B). Switching projects would result in a permanent exit of the disaster environment. The efficiency of working in the hypothetical alternative region varied for each agent in the disaster environment, and was uniformly distributed (0,1).

$$D_6 = 0.907 - 0.077x_{6,1} + 0.009x_{6,2} - 0.035x_{6,3} + 0.068x_{6,4} + 0.184x_{6,5} - 0.001x_{6,6} - 0.140x_{6,7} + 0.088x_{6,8} \quad (9)$$

The model was trained on a dataset with 3500 data points and tested on a separate set of about 1800 data points. The model accurately predicted the participant's decision 89% of the time. It is important to note that in the discussion of the different variables, many are duplicates from Experiment 5, except they use a fixed alternative region instead of a dynamic secondary disaster. As a result, the discussion here is limited and primarily references parallel variables in Experiment 5.

- Log of Decision Periods in Disaster $x_{6,1}(p < 0.001)$: Calculated as $\ln(t)$. The negative value of $c_{6,1}$'s meaning is similar to the insight gained from variable $x_{5,1}$.
- Remaining Need Factor for Region A Aid $x_{6,2}(p = 0.04)$: Calculated as

  $$\frac{H_{1,t}}{\sum_{i=0}^{I}\left(S_i W_{1,0}\right)}.$$

  The positive value of $c_{6,2}$ indicates that the fewer agencies that were responding in region A relative to the amount of need, the more likely a decision maker was to stay. This is a logical but important component of a decision maker's thought process, and is consistent with a decision maker's attempt to gain the maximum impact by avoiding competition.
- Ratio of Remaining Region A Need $x_{6,3}(p = 0.013)$: Calculated as

  $$\frac{H_{1,t}}{H_{h,0}}.$$

  The negative value of $c_{6,3}$'s meaning is parallel to that discussed for $x_{5,6}$.
- Normalized A Impact $x_{6,4}(p > 0.001)$: Calculated as

  $$\frac{W_{1,t}}{W_{1,0}}.$$

  The positive value of $c_{6,4}$'s meaning is parallel to that discussed for $x_{5,9}$.
- Normalized B Impact $x_{6,5}(p = 0.013)$: Calculated as

  $$R_i = \frac{W_{2,t}}{W_{2,0}}.$$

  The positive value of $c_{6,5}$ is interesting because it does not match with the discussion for $x_{5,10}$. It is important to note that this value was fixed throughout the experiment, while it was dynamic in Experiment 5. The intuitive and obvious result is that the fixed alternative impact in a different region is a significant decision factor for leaving the current disaster area.
- Normalized Average A Impact $x_{6,6}(p = 0.0334)$: Calculated as

  $$\frac{Avg_t\left(W_{1,t-1}\right)}{W_{1,0}}.$$

  The negative value of $c_{6,6}$ is very counterintuitive; it indicates that the higher the average impact in region A for all previous periods, the more likely a decision maker is to leave. This is somewhat consistent with the findings from the other experiments (that decision makers were likely to be wary of consistently high impacts) and matches well with the insight gained from the coefficient $c_{6,2}$.
- Normalized Average+Standard Deviation Impact A $x_{6,7}(p < 0.001)$: Calculated as

  $$\frac{Avg_t\left(W_{1,t-1}\right) + StDev_t\left(W_{1,t-1}\right)}{W_{1,0}}.$$

  The negative value of $c_{6,7}$ indicates that when a decision maker considered a fixed alternative impact, a high degree of variance was undesirable.
- Log of Ratio of A to B Impact in Previous Period $x_{6,8}(p = 0.001)$: Calculated as

  $$\ln\left(\frac{W_{1,t-1}}{W_{2,t-1}}\right).$$

  The positive value of $c_{6,8}$ indicates that the decision maker was more likely to stay in the current region unless there was a significant advantage to staying in the alternative region, based on the previous period's impact.

6. Conclusion

The optimal mix of partners for an agency operating in a disaster is highly dependent on the desired activity and the time of entry into a disaster area. The most important factor for understanding how agencies will behave in a disaster relief operation is learning about the people making the decisions. However, the reality of the disaster relief world is that capturing data, decisions, and outcomes is extremely difficult, but the need for an improved understanding has only increased. The use of interviews and experiments to build models of individual behavior in response to disaster provides a unique approach to fill this critical gap in knowledge.

This paper provided a new approach to designing, capturing, and developing decision models that can be used to simulate disaster relief operations. Building on information from interviews and current literature on disaster operations, we developed and executed six experiments to ascertain how people responded to decision trade-offs. In each experiment, we gathered a wide range of data to understand what factors most influenced decision-making. The results of these experiments provided data to build simulations of how networks of agencies might respond to a disaster, and how they would interact with one another in the process.

6.1. Key results

While there are a large number of results that have implications for disaster relief simulation (see Section 5 for discussion), here we highlight key lessons that can be learned from each of the six experiments:

1. *Receiving Offers from Other Agencies:* Decision makers prefer to delay commitment until they are forced to make a decision due to worsening options, or receive an excellent offer. The minimum value of an acceptable offer drops to the break-even point as opportunities become more scarce.
2. *Making Offers to Other Agencies:* Decision makers are more likely to look for partners the less efficient their own agency was. Additionally, the worse the current set of partnerships, the more willing the decision maker was to keep looking for new partners, as long as there had been at least 1 successful previous partnership.
3. *Resource Allocation:* Decision makers were highly prone to the sunk-cost fallacy such that the more invested they were in a particular type of aid, the more willing they were to take worse outcomes rather than change their investments. Additionally, they were very reticent to believe that any observed high returns could be sustained, further solidifying their bias towards current investments.
4. *Partnership Length:* Sunk-cost fallacy played heavily in a decision maker's choice of when to end a partnership: the larger the investment in the partnership the longer it would last irrespective of a worse payoff. Additionally, the larger the size of the disaster, the longer a decision maker would put up with poor impact. However, once a player began ending partnerships, they tended to end a whole set of partnerships simultaneously and go “all in”, in terms of a strategy shift.
5. *Ending Project:* Decision makers were consistently willing to weather losses temporarily rather than end a project with the first poor return. Similarly, the larger the initial disaster, the longer a decision maker was willing to sustain poor returns before ending a project.
6. *Time to Cease Operations:* The key lesson from this experiment was that decision makers are much less likely to leave a disaster operation altogether, the smaller the number of agencies responding. The main factor that resulted in an agency leaving altogether was a significant and sustained alternative impact somewhere else.

6.2. Study limitations driving future work

It is important to note that the approach presented is not a silver bullet for all behavior-modeling in disaster operations. However, the work presented provides a spring-board for a broad range of work in this area. In this section, we enumerate the limitations of the current work, highlighting each limitation as an opportunity for future work in the area.

1. *Relative Inexperience:* The experiments and resultant models for predicting decision behavior were entirely based on student participants. While there are a large number of people that volunteer and participate in disaster relief that do not have experience, an important extension of this research is to expand the set of participants to experts in the domain.
2. *Situational Variation:* The emphasis of the presented experiments was to understand how people might behave without specific context to the disaster. However, the reality of disaster operations is that there are major categories of disasters (e.g., tornado vs. hurricane) where the best response is different. This is an excellent opportunity for additional work to identify how people behave differently depending on the specifics of an actual disaster scenario.
3. *Political Isolation:* Decisions by disaster relief agencies (especially large ones such as the Red Cross) are not made in isolation from political pressure and fall-out. Capturing how decisions may change when this aspect of pressure is incorporated would be very interesting to perform when repeating the experiments in different scenarios with domain experts.
4. *Experimental Simplicity:* The experimental models focused on the minimum number of projects types (i.e., A vs. B), a linear size scale (i.e., 1–10) and other assumptions to make the experiment clear. This is a significantly limiting factor, especially given the wide range of project options in a disaster environment, but was necessary to minimize bias of expertize among the presented participant set. In future work, expanding the scope and complexity of the models could be done to better understand the decision models that are employed in the real world.
5. *Organizational Complexity:* In this work, we focused on understanding how an individual selects an option, but did not explore the dynamics of an organization as a complex set of individuals with conflicting objectives and personalities. For the scope of this work, we were focused on developing decision models for agencies, such that these models could be used to simulate agency behavior when interacting with one another. A more complex simulation/modeling approach would model people, with organizations as social constructs that execute decisions based on interaction, rather than treating the organization as a single top-down decision maker.
6. *Testing in Network:* The decision models developed here provide key components needed to build scenarios with built-in decision-making frameworks for agents in a simulated environment. To validate this approach, it is critical to test the implementation of the models in agent-based or Monte-Carlo simulation, where we can examine some of the additional dimensions in the problem of disaster coordination.
7. *Variable Independence:* Each variable of the decision models presented in Section 5 was discussed independently. As part of the ongoing work in model development, validation, and verification, the mediation and moderation effects will be studied in concert with testing in a simulated environment to examine how the different decision models impact an agency's behavior over time.

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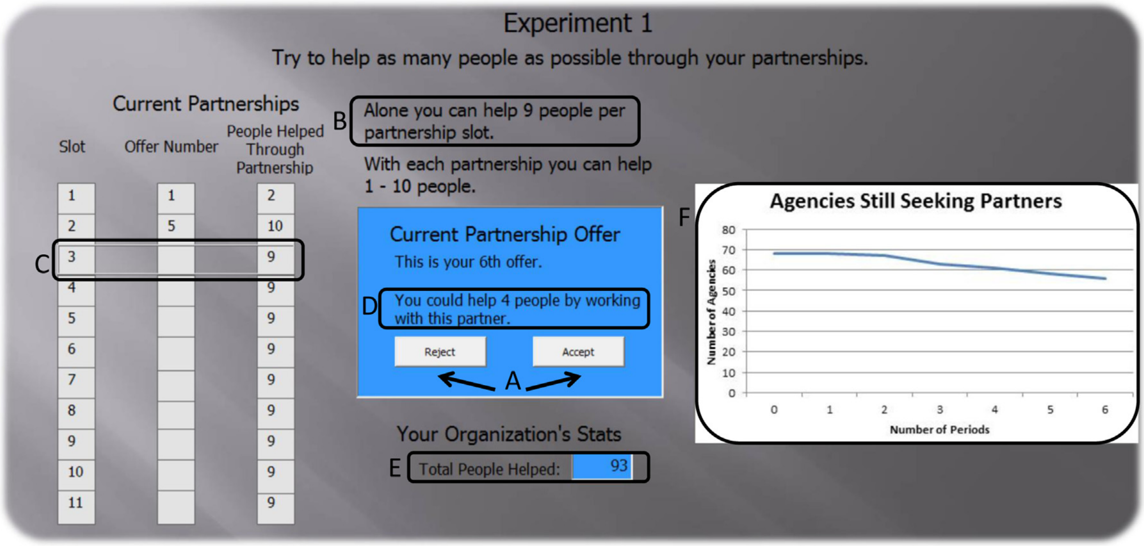

Fig. 3. Screenshot of Experiment 1 Interface. The key aspects of the interface are labeled A–F.

Appendix

Experiment 1: receiving offers from other agencies

The components of Experiment 1, shown in Fig. 3, are as follows: (A) The participant had to choose whether to accept or reject an offer from another agency in the region; (B) the participant was told how many people he/she could help without a partner; (C) the participant was shown the pertinent partnership slot; (D) the participant was told how many people could be assisted by accepting the current partnership offer; (E) the participant was told how many people the current set of decisions would assist; and (F) the participant was shown a dynamically updating graph of how many other agencies remained in the disaster area that could make an offer of partnership.

The experiment ended when all partnership slots were filled or all potential partners had left the pool of available agencies (seen in Fig. 3, part F).

Experiment 2: making offers to other agencies

The components of Experiment 2, shown in Fig. 4, are as follows: (A) The participant had to invest another resource in search of a partner or stop looking for partners for the remainder of the trial; (B) the participant was told the agency size that a potential partner would see when an offer was made; (C) the participant was shown the pertinent partnership slot, including the information about an alternative impact if no partners were sought; (D) the participant was told how many people he/she had helped with the last attempted partnership; (E) the participant was reminded how many people would be helped with the current decision set; and (F) the participant was shown a dynamically

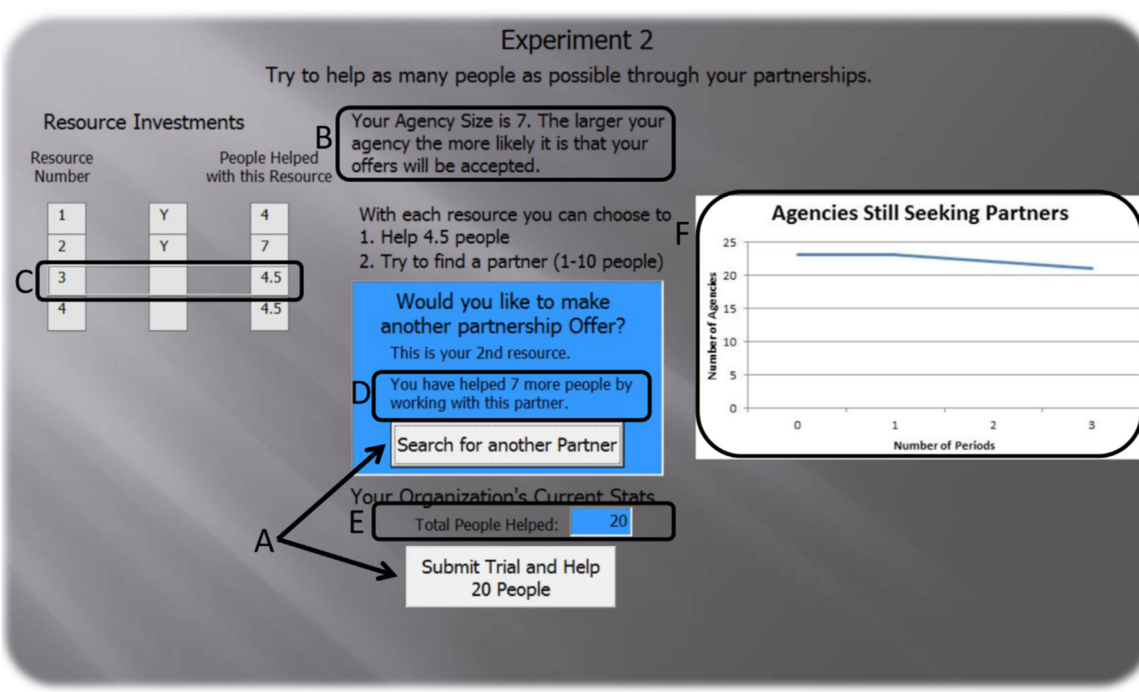

Fig. 4. Screenshot of Experiment 2 Interface. The key aspects of the interface are labeled A–F.

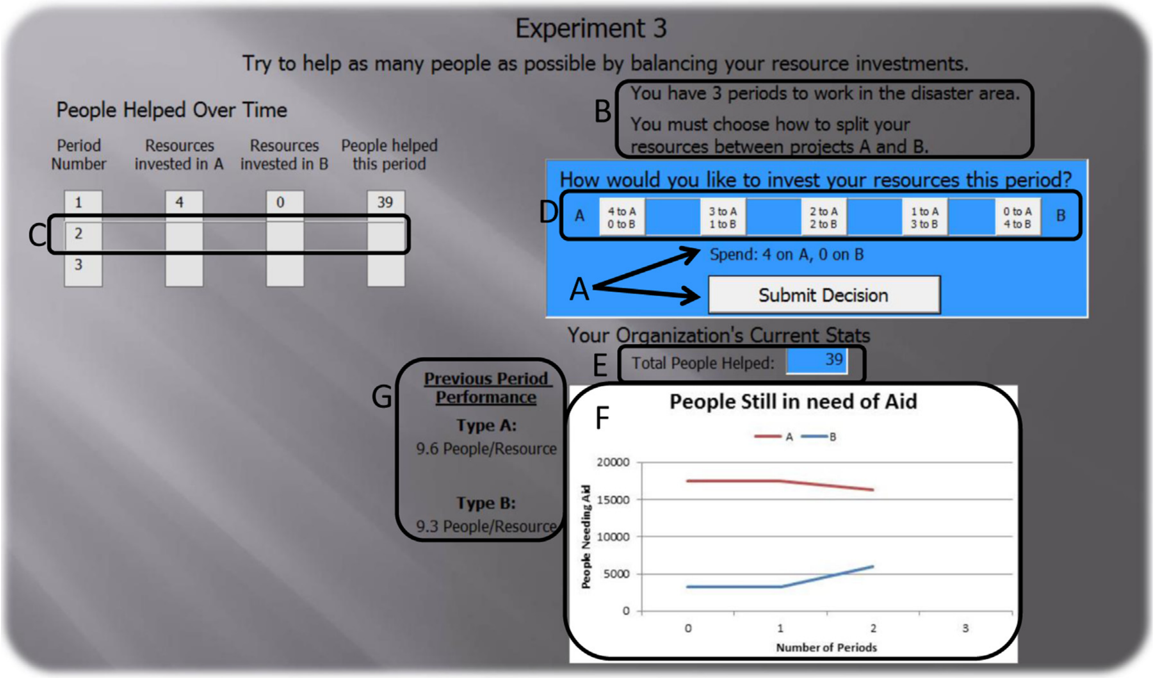

Fig. 5. Screenshot of Experiment 3 Interface. The key aspects of the interface are labeled A–G.

updating graph of how many other agencies remained in the disaster area that could receive an offer of partnership.

Experiment 3: resource allocation

The components of Experiment 3, shown in Fig. 5, are as follows: (A) The participant had to choose how many resources to invest in Projects A vs. B; (B) the participant was reminded of how many decision periods remained; (C) the participant was shown the pertinent partnership slot; (D) the participant was given several options for how to split resources between Projects A and B; (E) the participant was told how many people had already been assisted; (F) the participant was shown a dynamically updating graph of how many people needed aid for Projects A and B; and (G) the participant was shown the resource impact from the previous period.

Experiment 4: partnership length

The components of Experiment 4, shown in Fig. 6, are as follows: (A) The participant had to choose whether to continue or end a partnership in a given period; (B) the participant was reminded how many periods remained in the current trial; (C) the

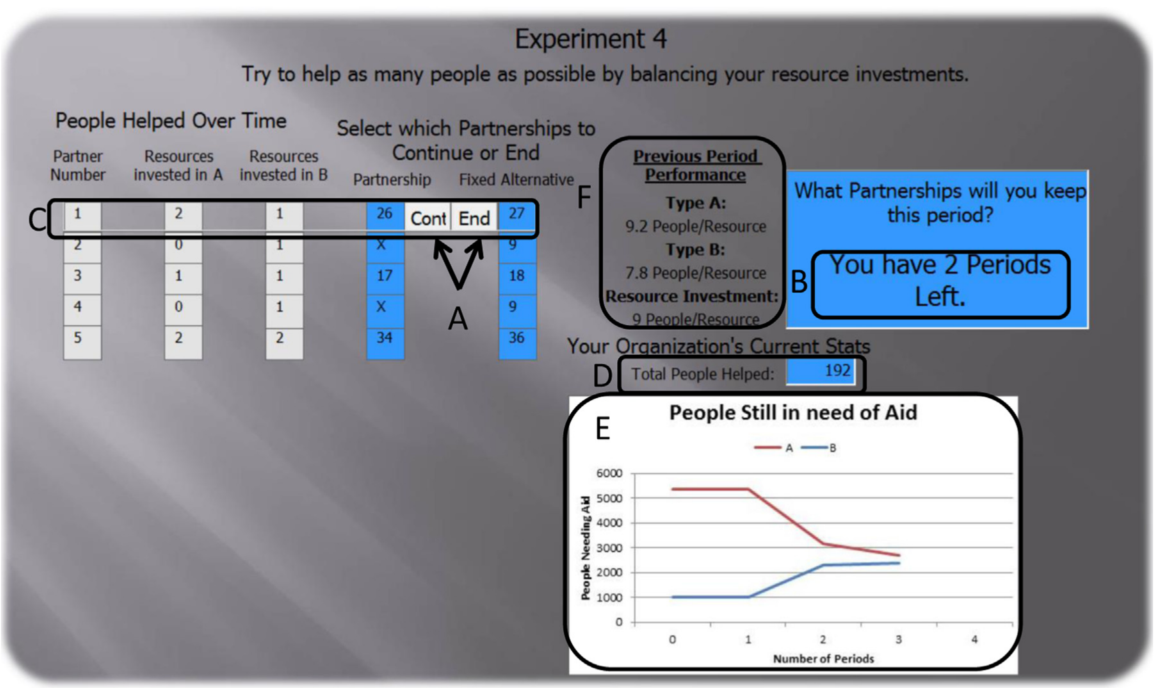

Fig. 6. Screenshot of Experiment 4 Interface. The key aspects of the interface are labeled A–F.

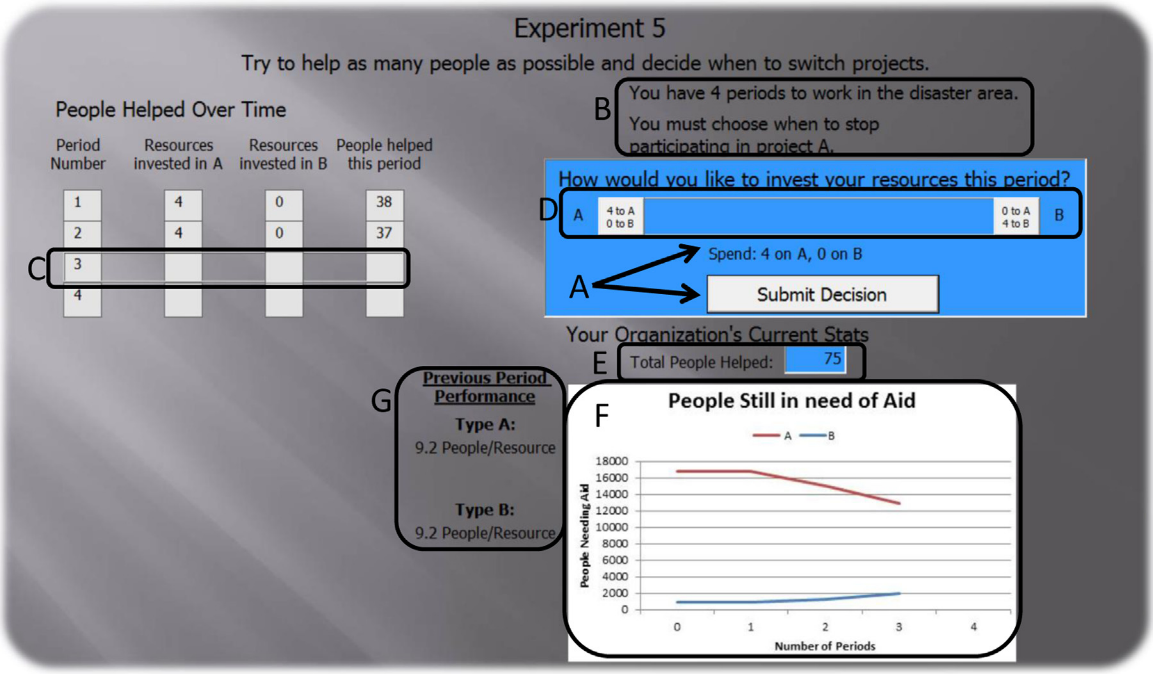

Fig. 7. Screenshot of Experiment 5 Interface. The key aspects of the interface are labeled A–G.

participant was shown the pertinent partnership slot, including information about how many resources the partner had invested in Projects A and B, as well as how many people had been helped in the previous period when compared with a fixed alternative (based on the number of resources in the partnership); (D) the participant was told how many people had already been assisted; (E) the participant was shown a dynamically updating graph of how many people needed aid for Projects A and B; and (F) the participant was shown the resource impact from the previous period, including the projected impact of the fixed alternative.

Experiment 5: ending projects

The components of Experiment 5, shown in Fig. 7, are as follows: (A) The participant had to choose how long to invest in Project A before permanently switching to Project B; (B) the participant was reminded that he/she could split resources for a set number of periods; (C) the participant was shown the pertinent decision slot; (D) the participant was given two resource allocation options; (E) the participant was told how many people had already been assisted; (F) the participant was shown a dynamically updating graph of how many people needed aid for Projects A and B; and (G) the participant

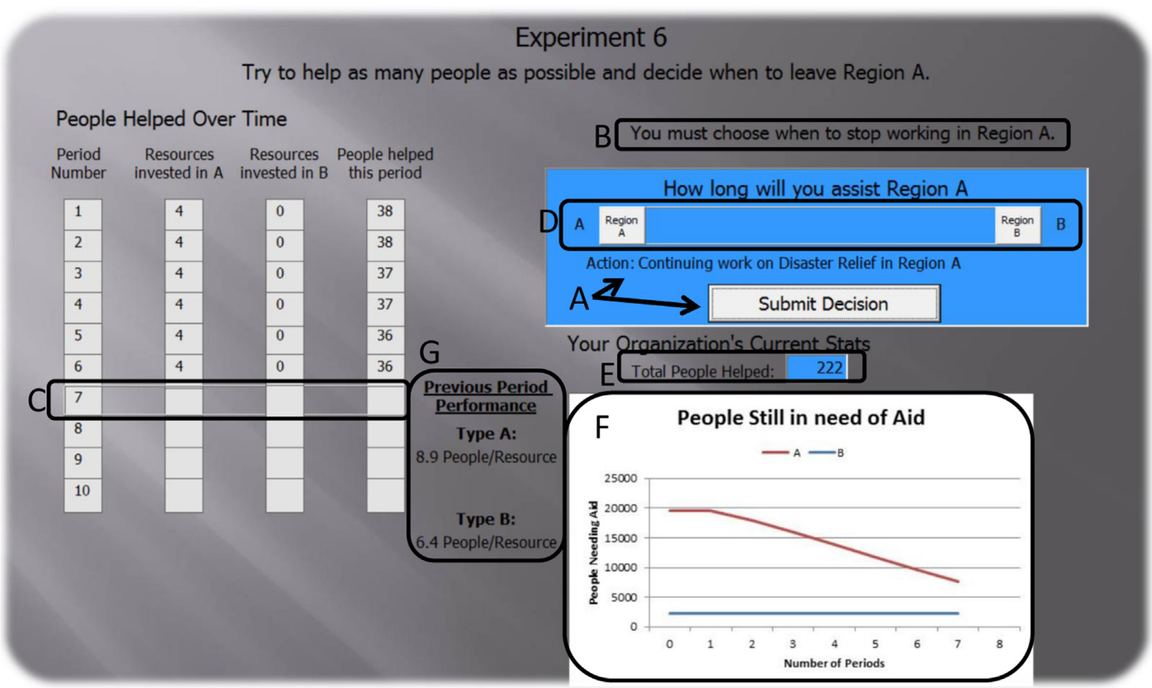

Fig. 8. Screenshot of Experiment 6 Interface. The key aspects of the interface are labeled A–G.

was shown the resource impact from the previous period.

Experiment 6: time to cease operations

The components of Experiment 6, shown in Fig. 8, are as follows: (A) The participant had to choose how long to invest in Region A before permanently switching to Region B; (B) the participant was reminded that he/she could split resources for a set number of periods; (C) the participant was shown the pertinent decision slot; (D) the participant was given two resource allocation options; (E) the participant was told how many people had already been assisted; (F) the participant was shown a dynamically updating graph of how many people needed aid for Projects A and B; and (G) the participant was shown the resource impact from the previous period for Project A, and a fixed return for Project B.

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