Modeling the Absence of Framing Effect among Indian and US populations in an Experience-based COVID-19 Disease Problem

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Abstract. Prior research in the decision from experience (DFE) has investigated the absence of framing effect in experience. However, it remains to be investigated how different cognitive models may account for human experiential choices in a pandemic situation like COVID-19 across two nationalities. The primary objective of this paper is to develop and analyze Instance-based Learning Theory (IBL) models, Q-Learning models, and ensemble models in their ability to predict human choices in different problem frames across two different nationalities. Human data were collected by recruiting one hundred sixty participants from India (80) and the USA (80) on a modified form of an Asian Disease Problem posing about the COVID-19 pandemic across four between-subject conditions that differed in problem frame (loss/gain) and nationality (India/USA). IBL and Q-learning models were developed and calibrated to the data obtained in the gain and loss problems across both nationalities. An IBL model with ACT-R default parameters was also considered. Furthermore, a model ensembling the predictions of Q-learning and IBL models was developed and calibrated to human data. Results revealed that the IBL model and the ensemble model with calibrated parameters explained human choices more accurately compared to the calibrated Q-learning and IBL models with ACT-R default parameters. We highlight the main implications of our findings for the cognitive modeling community.

Keywords: COVID-19 Disease Problem; Decision from Experience; Framing Effect; Instance-based Learning Theory; Q-Learning Model

1 Introduction

In the grievous times of the COVID-19 pandemic, cognitive errors and biases may distract leaders against optimal policymaking, and it may deter citizens from taking steps that promote their own and others' interests. Some of the cognitive biases like the framing effect may be pervasive [1], and these biases may play a significant role in influencing people's choices based upon how information is presented [2]. Prior research has experimented with the framing effect in the Asian disease problem (ADP), where the problem was presented in gain and loss frames either in a descriptive format (description) or experiential format (experience) to participants [13-15]. The main result was the presence of the framing effect (i.e., a preference reversal) between gain and loss problems in description and its absence in experience. Prior research has also investigated the existence of the framing effect among the Indian population in descriptive problems with an applied disease context in a COVID-19 disease problem (CDP) and the absence of the framing effect in the experiential format [16]. However, little is known about the existence of the framing effect in CDP with an applied disease context in the experience format across two nationalities such as India and the USA. Also, little is known about how computational cognitive models could account for the absence of the framing effect in applied disease contexts in the experience format across two different nationalities.

The decision from experience (DFE) research has focused on explaining human choices based upon their experience with the sampled information [3]. In particular, the sampling paradigm has been used to develop computational cognitive models of human choice behavior both at the individual level [4] and at the aggregate level [5-7]. Using the sampling paradigm, cognitive models have also been developed in abstract and applied domains [8]. For example, the Instance-Based Learning (IBL) model is a popular DFE algorithm for explaining aggregate and individual human choices [4, 9-10]. The IBL model borrows its mechanisms like activations, retrieval from memory, and blending from the ACT-R framework [11], and it operates by storing and retrieving experiences (called instances) from memory [10]. Each instance's activation is used to calculate the blended values for each option, thereby helping the model to make a consequential choice.

In contrast to the instance-based models, exploration and exploitation-based models in reinforcement learning (e.g., Q-learning) have been proposed to account for human choice in the experience format [12]. Q-learning algorithm uses exploration and exploitation strategies to gather information and make consequential choices based upon maximizing Q values. For example, during restaurant selection, which involves a decision, we can choose 'Exploitation' and go to the most loved restaurant or one can do 'Exploration,' i.e., try at a new restaurant [12].

The need for robust computational models in the field of decision-making during these demanding times of pandemic and economic instability drives the motivation to focus on development, comparison, and analysis of computational cognitive models. This paper's primary objective is to address the above-mentioned literature gaps. Specifically, we compare the abilities of different computational cognitive models, i.e., the IBL model and the Q-learning model, to predict human consequential choice in CDP in an experiential format (sampling paradigm) across different nationalities. Finally, we develop and calibrate an ensemble model by combining the IBL and Q-learning models to predict the consequential human choice in CDP in experience across different nationalities.

In the following paper, first, we detail an experiment to investigate the framing effect in experience in the COVID-19 disease problem among participants from India and the US. Next, we describe IBL, Q-learning, and ensemble models and address the models' calibration techniques to capture the consequential choices in CDP. Next, we present the results of the models' evaluation and close the paper by discussing the implications of our results.

2 The COVID-19 Disease Problem (CDP) Experiment

A total of one hundred and sixty participants were recruited randomly from India (N=80) and the US (N = 80) via Amazon MTurk to participate in a disease study program. Participation was voluntary, where about 64% of participants were males, and the rest were females. Ages of participants ranged between 18 years and 70 years (Mean = 33 years and standard deviation = 11.3 years). Participants were from different education levels: 24% undergraduates and 76% of graduates. Discipline-wise, the demographics were the following: 44% possessed degrees in science, technology, engineering and management, and 56% possessed degrees in humanities and social sciences. Participants were compensated for a flat participation fee of INR 21 (~ USD 0.28). The participants' maximum time to finish the study was less than 10 minutes across both the conditions.

Participants were randomly assigned to one of the four between-subject conditions involving the CDP in experience: India-gain (N = 40), India-loss (N=40), US-gain (N=40), and US-loss (N = 40). In the India-gain and US-gain conditions, the problem was framed as "lives saved" whereas, in the India-loss and US-loss conditions, the problem was framed as "lives lost" (see Fig. 1 for the experience format used across different conditions).

Imagine that your country is preparing for an outbreak of the new coronavirus disease, which is expected to kill certain number of people in your country. In this task, you need to choose between different health programs designed to combat the coronavirus. Health programs are represented by buttons. By clicking on a program button below, you can gather information about the outcome of the program associated with the button (sampling phase). The outcome shown on a button option during the sampling phase will not affect the final result. Once you are satisfied with your sampling of the button programs, you may click the "Make Allocations for Real" button to enter the allocation phase. In the allocation phase, you need to decide one of the health programs (A or B) for real (one final time).

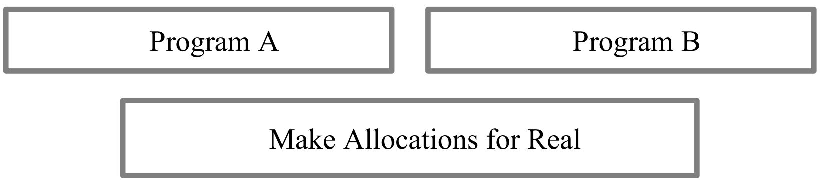

Fig. 1. The CDP presented to participants in the study in gain conditions.

As shown in Fig. 1, two programs (buttons), Program A and Program B, were presented to participants in different conditions. Participants could sample the program buttons by clicking on them as many times as they wished and, in any order, they desired before making a final choice for real. Upon clicking a program button, the system generated the outcomes in terms of the number of lives saved or lost (depending upon the gain or loss condition). The sampling in all the conditions was non-consequential, and the allocation of programs to buttons was randomized across participants in all the conditions. Participants could choose to end the sampling phase by clicking on the "Make Allocations for Real" button, which would redirect them to the allocation phase. In the allocation phase, participants were asked to make a consequential choice for one of the programs. In the gain conditions, program A was framed as "200 people will be saved" having a probability of 1, and program B was framed as "600 people will be saved" with 1/3rd probability or "No one will be saved" with 2/3rd probability. In loss conditions, program C was framed as "400 people will die" having a probability of 1, and program D was framed as "No one will die" with 1/3rd probability or "600 people will die" with 2/3rd probability. Participants were not told about the probability information on different program buttons. The outcomes generated during sampling and allocation phases were dependent on the probability of the outcome. As can be seen, programs A and C were identical and programs B and D were identical. In accordance with the findings of Gonzalez and Mehlhorn (2015) for ADP, we did not expect any difference in the proportion of A and C choice in the CDP among Indian and the US participants (i.e., we expected the absence of framing effect among participants of both the nationalities in the experience condition). We conducted a one-way ANOVA in gain and loss conditions with nationality as a between-subject factor, an alpha level of 0.05, and a power of 0.80 to test our expectations.

Results revealed that there was no significant difference between proportion of program A choices made by Indian and the US participants in the gain condition (India: 0.83 ~ US: 0.75; $F(1,78) = 0.281$, $p = .60$, $\eta^2 = 0.004$). Similarly, no significant difference in the proportion of program C choices between participants of both the nationalities was found in the loss condition (India: 0.70 ~ US: 0.78; $F(1,78) = 0.571$, $p = .45$, $\eta^2 = 0.007$). Thus, as per our expectation, an absence of framing effect in CDP in experience was seen irrespective of participant's nationality.

3 The Models

This section details the working of the IBL model, the Q-learning, and the ensemble models, which were developed and calibrated to account for human choice in the CDP in experience format across different nationalities.

3.1 Instance-Based Learning (IBL) model

The IBL model [7, 11-12] is built upon the ACT-R cognitive framework [11]. In this model, all the occurrences of an outcome of an option choice are stored in the memory in the form of instances. An instance is made up of the following structure: situation-decision-utility, where the situation is the current situation (two option buttons on a computer screen), the decision is the decision made in the current situation (choice for one of the option buttons), and the utility is the goodness of the made decision (the outcome obtained upon choosing an option). For making a final choice, all the instances belonging to an option are retrieved from the memory and blended on each option. The blended value of an option is a function of the activation of instances and their probability of retrieval from memory. The blended value of option *j* at any trial *t* is defined as:

$$V_{j,t} = \sum_{i=1}^{n} p_{i,j,t}\, x_{i,j,t} \tag{1}$$

where $x_{i,j,t}$ is the value of the utility part of an instance *i* on option *j* at trial *t*. The $p_{i,j,t}$ is the probability of retrieval of instance *i* on option *j* from memory at trial *t*. Because $x_{i,j,t}$ is the utility of an instance *i* on option *j* at trial *t*, the number of terms (*n*) in the summation in equation 1 changes when new outcomes are observed during sampling on the option *j*. For example, if *j* is an option with two possible outcomes, then $n = 1$ when one of the outcomes has been observed on the option (i.e., one instance is created in memory) and $n = 2$ when both outcomes have been observed on the option (i.e., two instances are created in memory).

At any trial *t*, the probability of retrieval of an instance *i* on option *j* at trial *t* is a function of the activation of that instance relative to the activation of all instances (1, 2, … *n*) created within the option *j*, given by

$$p_{i,j,t} = \frac{e^{(A_{i,j,t})/\tau}}{\sum_{i=1}^{n} e^{(A_{i,j,t})/\tau}} \tag{2}$$

where τ, is random noise defined as $\sigma * \sqrt{2}$ and σ is a free cognitive noise parameter. The activation of an instance *i* corresponding to an observed outcome on an option *j* in a given trial *t* is a function of the frequency of the outcome's past occurrences and the recency of the outcome's past occurrences (as done in ACT-R). At each trial *t*, activation $A_{i,j,t}$ of an instance *i* on option *j* is

$$A_{i,j,t} = \sigma * \ln\left(\frac{1-\gamma_{i,j,t}}{\gamma_{i,j,t}}\right) + \ln \sum_{t_p \epsilon \{1..,t-1\}} \left(t - t_p\right)^{-d} \tag{3}$$

where, *d* is a free decay parameter; $\gamma_{i,j,t}$ is a random draw from a uniform distribution bounded between 0 and 1, for instance *i* on option *j* in trial *t*; and t_p is each of the previous trials in which the outcome corresponding to instance *i* was observed in the task. The IBL model has two free parameters that need to be calibrated: *d* and *σ*. The *d* parameter controls the reliance on recent or distant sampled information. Thus, when *d* is large (> 1.0), then the model gives more weight to recently observed outcomes in computing instance activations compared to when *d* is small (< 1.0). The *σ* parameter helps to account for the participant-to-participant variability in an instance's activation. We feed the sampling done by individual human participants to generate instances and compute blended values in the IBL model. During sampling, each time a choice is made, and the outcome is observed, the instance associated with it is activated (created or reinforced). At the final choice, blended values are computed and the model chooses the option with the highest blended value.

In one version of the IBL model, we used the default values of the ACT-R parameters, i.e., $d = 0.50$ and $\sigma = 0.25$ (IBL model with ACT-R parameters). These parameters show lesser reliance on recency and frequency of information and a reasonable participant-to-participant variability in consequential choices. However, in a second version of the IBL model, we found single values for the two parameters (d and σ) by calibrating them to individual participant consequential choices in gain and loss conditions, respectively. We refer to this model as the IBL model with calibrated parameters and, for the parameters' calibration, we determined a model choice and compared this choice to a human participant's choice. In order to create exploration of options during sampling, the model's memory was pre-populated with 2 instances (i.e., one on each option) with a 1000 utility. This value of utility was higher than all possible outcomes in the different options. These pre-populated instances may represent the initial expectations that participants may bring to the task [10]. If the model's choice equaled human participant's choice, then the dependent variable (error) was coded as zero; otherwise, the error was coded as one. We minimized the average of errors across all participants in the calibration process separately across the four between-subject conditions.

3.2 Q-learning model

Q-learning is a model-free learning algorithm, i.e., a reinforcement algorithm which uses a trial-and-error technique instead of transition probability distribution associated with the Markov decision process (MDP). Its objective is to select optimal action associated with the maximum available reward. The algorithm maintains a Q-table consisting of states and actions as rows and columns, respectively. It calculates the rewards associated with each action in a state. Initially, the whole matrix (Q-table) is initialized to zero. The Q value of action A_t in a state S_t is determined by the following equation:

$$Q_{St,At} = Q_{St,At} + \alpha\left(r_t + \gamma\left(\begin{matrix} max \\ \alpha \end{matrix} Q_{St+1,A}\right) - Q_{St,At}\right) \tag{4}$$

where, $Q_{St,\,At}$ is the Q value for a given state S_t and an action A_t at time t. The r_t is the reward observed on taking action A_t. Here, α represents the learning rate, i.e., how quickly the model learns the optimal policy. For $\alpha = 0$, the Q-value will never be updated, and all the rewards will be set to 0. Hence learning never happened. The discount factor γ allows us to decide the importance of possible future rewards compared to the present reward. For a given state S_t at time t, the most suitable action is the one which has the highest Q value.

For CDP, the set of actions included $A_t \in$ {Program A, Program B} for India-Gain and US-Gain conditions and $A_t \in$ {Program C, Program D} for India-Loss and US-Loss conditions. The learning rate parameter was calibrated to minimize the error ratio for all the conditions, separately. Since there was only one state available for each set of actions to explore, the discount factor (γ) was set to 0 for the algorithm to converge. Q-table was populated with the rewards associated with each program. In both the gain conditions, reward associated with program A, r_t = 200, was awarded when explored. There was a one-third probability that r_t = 600 will be awarded for program B and a two-third probability that r_t = 0 will be awarded. Similarly, in both the loss conditions, the reward associated with program A was r_t = -400. For program B, there was a one-third probability that r_t = 0 will be awarded and a two-third probability that r_t = -600 would be awarded. Lastly, the model made a final choice by selecting the option associated with the maximum reward in the Q-table.

3.3 Ensemble model

In ensemble modeling, multiple modeling algorithms are used to predict an outcome by aggregating each base model's prediction [17]. Thus, the ensemble model combines the best out of its base models. For CDP, we developed an ensemble model that used the IBL and the Q-learning models as its base models to predict model choice in gain and loss conditions for both nationalities. The *w* parameter was used to assign a weight to the base models to predict the model's outcome. The ensemble model was calibrated to minimize the error ratio in each of the four conditions, separately. To calculate the probability of choosing an option as the ensemble model's choice, the following equation was used:

$$E_t = w * IBL_t + (1 - w) * QL_t \tag{5}$$

where E_t represents the probability of option *t* being chosen as the final option by the ensemble model, *w* is the weight parameter, IBL_t is the probability of *t* being chosen as the final option by the IBL model, and QL_t represents the probability of *t* being chosen as the final option by the Q-learning model. Here, the weight parameter (*w*) represents each base model's contribution to the final prediction of the ensemble. In this paper, higher values of *w* represent the higher contribution of the IBL model in the final prediction. The contribution of the Q-learning model in ensemble prediction will be 1-*w*. The probabilities of IBL_t and QL_t are calculated by using blended values and Q values of each option in the IBL model and Q-learning model, respectively. The option with higher E_t value among program A (or C) and program B (or D) would finally be chosen as the model choice.

4 Method

4.1 Dependent Variables

We ran the models for as many times as there were human participants in the four conditions independently. To compare human and model choices, we evaluated an "error ratio" (i.e., the ratio of incorrectly classified final choices between model and human participants divided by the total number of human participants). Thus, the error ratio was calculated as:

$$Error\ Ratio = (A_m B_h + B_m A_h) / (A_m A_h + B_m B_h + A_m B_h + B_m A_h) \tag{6}$$

where, A_mB_h was the number of participants where the model predicted an A (or C) program choice but human made a B (or D) program choice. B_mA_h was the number of participants where the model predicted a B (or D) program choice but the human player made an A (or C) program choice. Similarly, the A_mA_h and B_mB_h were the number of participants where the model predicted the same choice as made by the human participant. The smaller the value of error ratio, the more accurate is the model in accounting for individual choices in CDP.

4.2 Model Calibration

The two free parameters of the IBL model, d and σ, were calibrated using a genetic algorithm program in all four between-subject conditions separately. The genetic algorithm repeatedly modified a population of individual parameter tuples to find the tuple that minimized the error ratio in a condition. Both d and σ parameters were varied in the range [0, 10]. The population size used here was a 20 randomly selected parameter tuples in a generation (each parameter tuple was a particular value of d and σ). The mutation and crossover fractions were set at 0.1 and 0.8, respectively, to optimization over 150 generations. For each parameter tuple, the IBL model was run ten times across the 40 human participants per condition to account for run-to-run uncertainties present in the model.

Similarly, the Q-learning model's learning rate parameter (α) was calibrated for all four between-subject conditions using a genetic algorithm program. It was varied in the range of [0, 1]. The population size used here was a 20 randomly selected parameter tuples in a generation (each parameter tuple was a particular value of α). The mutation and crossover fractions were set at 0.1 and 0.8, respectively, to optimize over 150 generations. For each parameter tuple, the Q-learning model was run ten times across 40 human participants per condition to account for run-to-run uncertainties present in the model. Also, the ensemble model's weight parameter (w) was calibrated using the genetic algorithm. It was also varied in the range of [0, 1] in all four conditions. The ensemble model was run ten times across 40 human participants of each condition per parameter tuple to account for all the uncertainties of the model. Across the ten runs, the average error ratio was computed for all the models, separately, by averaging the error ratios from each run, and it was minimized.

5 Results

5.1 Human and Model Results

The proportion of A choices (India-gain & US-gain conditions) and the proportion of C choices (India-loss & US-loss conditions) from human data, IBL model with calibrated parameters, Q-learning model, ensemble model with calibrated parameters, and IBL model with ACT-R default parameters is shown in Fig. 2 (a) and Fig. 2 (b).

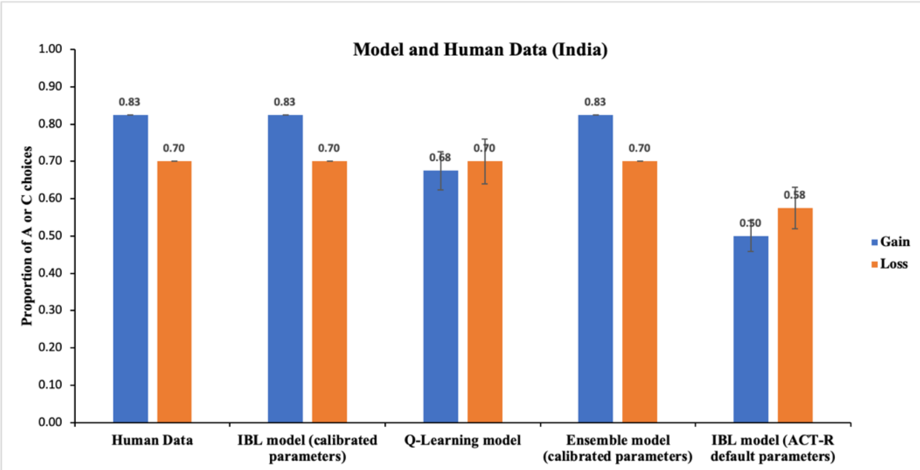

Fig. 2. (a). The proportion of A choice (India-gain condition) or C choices (India-loss condition) in human data, calibrated IBL model, Q-learning model, calibrated Ensemble mode, and IBL model with ACT-R default parameters. The error bars show 95% CI around the average estimate.

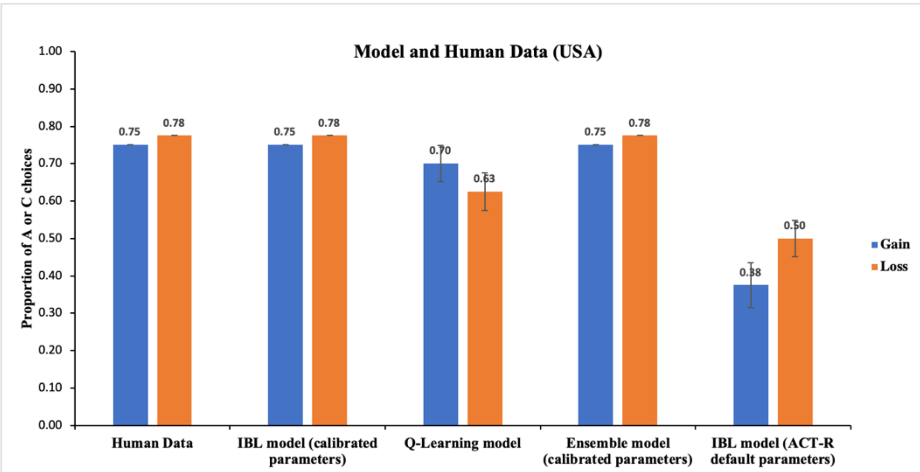

Fig. 2. (b). The proportion of A choice (US-gain condition) or C choices (US-loss condition) in human data, calibrated IBL model, Q-learning model, calibrated Ensemble mode, and IBL model with ACT-R default parameters. The error bars show 95% CI around the average estimate.

The IBL models, Q-learning models, and ensemble models were calibrated against human choices in all four conditions. The MSD values between human choice and the IBL calibrated model choice were 0.00 in all four conditions. Whereas, the MSD values between human choices and Q-learning model choice were 0.35 for India-Gain, 0.42 for India-Loss, 0.38 for US-Gain, and 0.37 for US-Loss. Thus, the IBL model explained human choices better than the Q-learning model in all four conditions.

Table 1 shows the best-calibrated parameters in different models across the four between-subject conditions. In the IBL model, a large *d* value represents excessive reliance on model recency during sampling. Also, the smaller σ value represents lesser participant-to-participant variability in instance activations.

Table 1. Model parameters across all four between-subject conditions

Conditions	**IBL (calibrated)**	**Q-learning**	**Ensemble**	**IBL (ACT-R)**
India-Gain	d = 7.05 & σ = 0.07	α = 0.47	w = 0.56	d = 0.50 & σ = 0.25
India-Loss	d = 9.70 & σ = 0.22	α = 0.42	w = 0.72	d = 0.50 & σ = 0.25
US-Gain	d = 6.98 & σ = 0.13	α = 0.62	w = 0.51	d = 0.50 & σ = 0.25
US-Loss	d = 6.86 & σ = 0.13	α = 0.53	w = 0.78	d = 0.50 & σ = 0.25

Tables 2 and 3 show the individual-level results from different models in all four conditions. For IBL models with calibrated parameters, the same results were obtained across 10-runs of the models, and there was no deviation in the mean-percentages. The calibrated IBL models produced 0.0% of A_mB_h and B_mA_h combination, i.e., the incorrect combinations, in India-Gain, India-Loss, US-Gain, and US-Loss conditions. Therefore, according to equation 6, the calibrated IBL models demonstrated 100% accuracy in both the conditions, across both nationalities. In the case of Q-learning, 10-runs of all the models were performed, and the average percentage and deviation from the mean percentage were calculated. In the India-Gain condition, the Q-learning model produced a 35% error, while in the India-Loss condition, a 45% error was produced. Similarly, in the US-Gain condition, the Q-learning model produced a 40% error, and in the US-Loss condition, a 50% error was produced.

Table 2. The error ratios from different models in the India-Gain and India-Loss conditions

Human and Model data combination	IBL Gain	IBL Loss	Q-L Gain	Q-L Loss	Ensemble Gain	Ensemble Loss	ACT-R Gain	ACT-R Loss
A_mA_h %	82.5	70.0	57.5	47.5	82.5	70.0	45.0	32.5
B_mB_h %	17.5	30.0	07.5	07.5	17.5	30.0	12.5	05.0
A_mB_h %	00.0	00.0	10.0	22.5	00.0	00.0	05.0	25.0
B_mA_h %	00.0	00.0	25.0	22.5	00.0	00.0	37.5	37.5
Error Ratio	0.00	0.00	0.35	0.45	0.00	0.00	0.43	0.63

Table 3. The error ratios from different models in the US-Gain and US-Loss conditions

Human and Model data combination	IBL Gain	IBL Loss	Q-L Gain	Q-L Loss	Ensemble Gain	Ensemble Loss	ACT-R Gain	ACT-R Loss
A_mA_h %	75.0	77.5	52.5	45.0	75.0	77.5	30.0	30.0
B_mB_h %	25.0	22.5	07.5	05.0	25.0	22.5	17.5	02.5
A_mB_h %	00.0	00.0	17.5	17.5	00.0	00.0	07.5	20.0
B_mA_h %	00.0	00.0	22.5	32.5	00.0	00.0	45.0	47.5
Error Ratio	0.00	0.00	0.40	0.50	0.00	0.00	0.53	0.68

The IBL model with ACT-R default parameters produced a 43% error in the India-Gain condition, a 63% error in India-Loss condition, a 53% error in the US-Gain condition, and a 68% error in US-Loss condition. The ensemble model also reported 100% accuracy in all four conditions as 0.0% error was produced in India-Gain, India-Loss, US-Gain, and US-Loss conditions (see Table 2 and 3).

Overall, the Q-learning and the IBL model with ACT-R default parameters performed poorly compared to the calibrated IBL model and the ensemble model.

6 Discussion & Conclusions

In this research, we compared the human choices made by participants belonging to different nationalities, i.e., India and the USA, by testing the effect of problem framing in specific disease contexts (e.g., COVID-19 disease problem) in experiential format. Our experimental results showed no difference in the proportion of program A and C choices across India and the US participants. This result seems to confirm the assumption that the absence of the framing effect in CDP in experience is uniform among people belonging to two different nationalities (India and USA). Also, this result was confirmed via cognitive modeling: the calibrated IBL model parameters possessed similar values across different conditions involving the two nationalities.

Furthermore, we compared two computational cognitive models, IBL and Q-learning, on COVID-19 Disease Problem involving DFE. Next, we developed ensemble models to aggregate the responses of the IBL models and the Q-learning models to predict the outcome similar to human decisions. Results revealed that IBL models with calibrated parameters could predict human choices with total accuracy, which was not the case with Q-learning models or IBL models with default ACT-R parameters.

The Q-learning model's poor performance in CDP follows from the fact that the Q-learning algorithm directly learns from optimal policy, and it aims to maximize the rewards irrespective of when the sample is presented during sampling. In contrast, the IBL model's high value of decay parameter revealed the model's dependence on the recency of sampled outcomes being presented.

The IBL model with calibrated parameters performed exceedingly better than the IBL model with ACT-R default parameters. This finding builds upon the works of Gonzalez and Mehlhorn (2015). These authors showed that in experience, the assumption of low recency and reasonable variability of default ACT-R might not exist, and people's deterministic final choices may be driven by excessive reliance on recency and frequency of samples.

This paper took two computational cognitive models for study on DFE during a pandemic situation. Future investigation may be extended by involving different computational cognitive modeling frameworks such as Clarion, LIDA, and SOAR to test their abilities on real-world DFE problems. Also, various other social, cultural, and political factors may be considered for the investigation to test their influence on DFE in CDP. We plan to continue experimenting with some of these ideas as part of our future work in the decision from experience research.

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