Modeling the Absence of Framing Effect in an Experience-based Covid-19 Disease Problem

Neha Sharma (neha724@gmail.com)
School of Computing, Indian Institute of Information Technology Una, India – 177220

Shashank Uttrani (shashankuttrani@gmail.com)
Applied Cognitive Sciences Laboratory, Indian Institute of Technology Mandi, India – 175075

Varun Dutt (varun@iitmandi.ac.in)
Applied Cognitive Sciences Laboratory, Indian Institute of Technology Mandi, India – 175075

Abstract

Prior research in decisions from experience (DFE) has investigated people's consequential decisions after information search both experimentally and computationally. However, prior DFE research has yet to explore how computational cognitive models and their mechanisms could explain the effects of problem framing in experience. The primary objective of this paper is to address this literature gap and develop Instance-based Learning Theory (IBLT) models on the effects of problem framing. Human data was collected on a modified form of the Asian disease problem posed about the COVID-19 pandemic across two between-subject conditions: gain (N = 40) and loss (N = 40). The COVID-19 problem was presented as "lives saved" in the gain condition and "lives lost" in the loss condition. Results revealed the absence of the classical framing effect, exhibiting no preference reversal between gain and loss conditions in experience. Next, an IBL model was developed and calibrated to the data obtained in the gain and loss problems. The calibrated model was generalized to the non-calibrated conditions (gain to loss and loss to gain). An IBL model with ACT-R default parameters was also generalized. Results revealed that the IBL model with calibrated parameters explained human choices more accurately compared to the IBL model with ACT-R default parameters. Also, participants showed greater reliance on recency and frequency of outcomes and less variability in their choices across both gain and loss conditions. We highlight the main implications of our findings for the cognitive modeling community.

Keywords: individual choice; experience; sampling; computational models; framing; gain; loss; COVID-19 disease problem.

Introduction

Whenever the world has seen new contagious diseases, medical practitioners have relied on their prior experience with treatments on other diseases to tackle the crises (HT, 2020). Depending upon the similarity and differences between prior experiences of diseases and a specific current disease, a combat plan may be selected for implementation. The act of making choices based upon prior experience, however, is not limited to making disease combat decisions; rather, it may be a very common exercise involving people in different facets of their daily life (choosing what to eat, whom to marry, or what career to pursue). Gaining experience via information search (or sampling) before a consequential choice forms an integral part of decisions from experience (DFE) research, where the focus is on explaining human decisions based upon one's experience with sampled information (Hertwig & Erev, 2009). DFE research has proposed a "sampling paradigm" (Hertwig & Erev, 2009), where people are presented with two or more options to choose between. These options are represented as blank buttons on a computer screen. People can sample as many buttons as they wish and in any order they desire (information search). Once people are satisfied with their sampling of the button options, they decide from which option to make a single consequential choice for real.

The sampling paradigm has been used to develop computational cognitive models of human choice behavior both at the individual level (Sharma & Dutt, 2017) and at the aggregate level (Busemeyer & Wang, 2000; Gonzalez & Dutt, 2012; Lejarraga, Dutt, & Gonzalez, 2012). In fact, using the sampling paradigm, cognitive models have also been developed in both abstract and applied domains (Sharma & Dutt, 2018). For example, the Instance-Based Learning (IBL) model is a popular DFE algorithm for explaining aggregate and individual human choices (Erev et al., 2010; Gonzalez & Dutt, 2011; Sharma & Dutt, 2017). The IBL model borrows mechanisms like activations, retrieval from memory, and blending from the ACT-R framework (Anderson & Lebiere, 1998) and it operates by storing and retrieving experiences (called instances) from memory (Gonzalez & Dutt, 2011). Each instance's activation is used to calculate the blended values for each option, thereby helping the model to make a consequential choices.

Although computational cognitive models have been developed in the DFE's sampling paradigm at the aggregate and individual participant levels in abstract and applied problem domains (Sharma & Dutt, 2017), yet little is known on how these models would account for human decisions driven by the problem's framing in experience in applied domains (Gonzalez, Dana, Koshino, & Just, 2005; Tversky & Kahneman, 1981). For example, in the famous Asian disease problem (ADP), participants are asked to imagine that a country is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people (Tversky & Kahneman, 1981). One group of people are presented this problem as a gain in terms of "lives saved;" whereas, a second group of people are presented the same problem as a loss in terms of “lives lost.” Although the gain and loss frames are equivalent, results reveal a framing effect: A large majority among those presented the gain frame choose the safe option; however, a large majority among those presented the loss frame choose the risky option. Gonzalez and Mehlhorn (2015) showed that the framing effect was present among people when they were presented with the ADP in a descriptive format; however, the framing effect disappeared in the experiential format (i.e., DFE’s sampling paradigm). Gonzalez and Mehlhorn (2015) went a step further and developed an IBL model with ACT-R parameters to explain the disappearance of the framing effect in experience. However, Gonzalez and Mehlhorn (2015) did not calibrate their model’s parameters as well as these authors did not test the framing effect in problems with a context (e.g., problem about the specific COVID-19 disease compared to the general Asian disease).

The primary objective of this research is to overcome the above-mentioned literature gaps. First, we evaluate the framing effect in experience among gain and loss problem frames in a COVID-19 disease problem (CDP). Next, we evaluate how an IBL model calibrated to the gain and loss frames explains the human choices in CDP. We also evaluate the generalization of IBL model parameters from the calibrated problem to the non-calibrated problem (gain problem’s parameters to the loss problem and loss problem’s parameters to the gain problem). For the purposes of our evaluations, the IBL model was exposed the sampling of participants and it predicted the consequential choices post sampling.

In what follows, first, we detail an experiment where we investigated the framing effect in experience in CDP. Next, we detail an IBL model and discuss the methodology of calibrating the model to capture the consequential choices in CDP. Next, we present the results of model’s evaluation both during calibration and during generalization. Finally, we close the paper by discussing the implications of our results.

The COVID-19 Disease Problem (CDP) Experiment

Eighty participants were recruited via Amazon MTurk in India to participate in a disease program study. Participation was voluntary, about 67% percent of participants were males, and the rest were females. Ages ranged from 18 years to 73 years (Mean = 32.55 years and standard deviation = 10.04 years). Participants were from different education levels: 19.4% undergraduates and 80.6% graduates. Discipline-wise, the demographics were the following: 31.25% possessed degrees in engineering, 10.62% possessed degrees in basic sciences, and 28.6% possessed degrees in humanities and social sciences. Participants were compensated a flat participation fee of INR 21 (~ USD 0.28). No participant took more than 10 minutes across both conditions to finish the study.

Participants were randomly assigned to one of two between-subject conditions involving the CDP in experience: gain (N = 40) and loss (N = 40). In the gain condition, the CDP was framed as “lives saved;” whereas, in the loss condition, the CDP was framed as a “lives lost” (see Figure 1).

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).

Program A | Program B

Make Allocations for Real

Figure 1. The CDP presented to participants in the study in gain condition.

As shown in Figure 1, in the gain condition, participants were presented with programs A and B, which they needed to sample as many times they desired and in any order they desired before making a final choice for real. In the loss condition, participants were presented with programs C and D, which they needed to sample as many times they desired and in any order they desired before making a final choice for real. The allocation of programs to buttons was randomized across participants in both conditions and sampling in both conditions was nonconsequential. At any time during the sampling phase, participants could click the “Make Allocations for Real” button (see Figure 1). Clicking the “Make Allocations for Real” button terminated the sampling phase and moved participants to the allocation phase. In the allocation phase, participants were asked to make a consequential choice for one of the programs. In the gain condition, program A was framed as “200 people will be saved” (1 probability) and program B was framed as “600 people will be saved” (1/3rd probability) or “No one will be saved” (2/3rd probability). In the loss condition, program C was framed as “400 people will die” (1 probability) and program D was framed as “Nobody will die” (1/3rd probability) or “600 will die” (2/3rd probability). In both conditions, the probability information was not shown, and it was only used to generate the outcomes in quotes above. As can be seen, programs A and C were identical and programs B and D were identical. In agreement with Gonzalez and Mehlhorn (2015)’s results for ADP, we expected no difference in the proportion of A and C choices in the CDP (i.e., we expected an absence of the framing effect). To test our expectation, we performed a one-way ANOVA with condition as a between-subjects factor, an alpha level of 0.05, and a power of 0.80.

Results revealed that there was no significant difference between the gain and loss conditions in the proportion of A or C choices (gain: 0.83 ~ loss: 0.70; $F(2,78) = 1.720$, $p = .19$, $\eta^2 = 0.02$). Thus, as per our expectations and contrary to the classical descriptive results, there was an absence of the framing effect in the experience-based CDP.

The Model

In this section, we detail the working of the IBL model that was developed to account for human choices in the CDP.

Instance-Based Learning (IBL) Model

The IBL model (Dutt & Gonzalez, 2012; Gonzalez & Dutt, 2011; 2012; Lejarraga, Dutt, & Gonzalez, 2012) is built upon the ACT-R cognitive framework (Anderson & Lebiere, 1998). In this model, instances are created in memory for each occurrence of an outcome on choice options. 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). When a choice is to be made, instances belonging to each option are retrieved from memory. These instances are then blended on each option. The blended value of an option is a function of activation of instances as well as their probability of retrieval from memory. The blended value of option j at any trial t is defined as:

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

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

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

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

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

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 participant's 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 prepopulated instances may represent the initial expectations that participants may bring to the task (Gonzalez & Dutt, 2011). If the model participant'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 gain and loss conditions.

Method

Dependent Variables

The model was run for as many model participants as there were human participants in the two 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:

$$\text{Error Ratio} = (A_mB_h + B_mA_h) / (A_mA_h + B_mB_h + A_mB_h + B_mA_h) \quad (4)$$

where, A_mB_h was the number of participants where the model predicted an A (or C) program choice but the 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 a 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 the error ratio, the more accurate is the model in accounting for individual choices in CDP.

Model Calibration

The IBL model described here possessed two free parameters d and σ. These parameters were calibrated using a genetic algorithm program in both gain and loss conditions separately. The genetic algorithm repeatedly modified a population of individual parameter tuples in order to find the tuple that minimized the error ratio in a condition. The d and σ parameters were both varied in the range [0, 10]. In each generation, the genetic algorithm selected individual parameter tuples randomly from a population to become parents and used these parents to select children for the next generation. Over successive generations, the population evolved toward an optimal solution. The population size used here was a set of 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, for an optimization over 150 generations. For each parameter tuple, the IBL model was run 10 times across the 40 human participants per condition to account for run-to-run uncertainties present in the model. Across the 10 runs, the model's average error ratio was computed by averaging the error ratios from each run and it was minimized. The parameter tuple that minimized the average error ratio across 150 generations were reported as the calibrated parameters for the IBL model.

Results

We evaluated the IBL model's ability to account for individual consequential choices in both gain and loss conditions separately. In the gain condition, the best-calibrated values of d and σ parameters were found to be 7.05 and 0.07, respectively. In the loss condition, the best-calibrated values of d and σ were found to be 9.70 and 0.22, respectively. A large d value exhibited excessive reliance on recency during sampling. Also, the smaller σ value exhibited lesser participant-to-participant variability in instance activations.

Table 1 shows the individual-level results from the gain and loss conditions. The same results were obtained across 10-runs of the model and there was no deviation in the percentages from the mean. As shown in Table 1, the calibrated IBL model in the gain condition produced 83% of A_mA_h combinations and 17% of B_mB_h combinations, respectively. In contrast, for the IBL model in the gain condition, the erroneous A_mB_h and B_mA_h combinations were both 0.0%, respectively. Based on these statistics, the IBL model showed 100% accuracy in the gain condition. Furthermore, the calibrated IBL model in the loss condition produced 70% of A_mA_h combinations and 30% of B_mB_h combinations, respectively. In contrast, for the IBL model in the loss condition, the erroneous A_mB_h and B_mA_h combinations were both 0.0%, respectively. Thus, again, the IBL model possessed 100% accuracy in the loss condition.

Table 1: The calibration results from the IBL model in the CDP.

Human and Model data combination H/M	Gain condition	Loss condition
Parameters	d = 7.05, σ = 0.06	d = 9.70, σ = 0.22
Number of participants	40[1]	40
A_mA_h percentage	83	70
B_mB_h percentage	17	30
A_mB_h percentage	00	00
B_mA_h percentage	00	00
Error Ratio	00	00

Note. [1] Each of the 10-runs of the model produced the same percentage with 0.0 as the standard deviation.

Table 2 shows the results of the IBL model in the CDP where the model possessed ACT-R default parameters (d = 0.5 and σ = 0.25).

Table 2: The IBL model in the CDP with ACT-R default parameters.

Human and Model data combination H/M	Gain condition	Loss condition
Parameters	d = 0.50, σ = 0.25	d = 0.50, σ = 0.25
Number of participants	40	40
A_mA_h percentage	41.6[1] (5.5)[2]	34.5 (5.9)
B_mB_h percentage	14.7 (3.0)	13.0 (2.6)
A_mB_h percentage	03.3 (3.0)	17.0 (2.6)
B_mA_h percentage	41.4 (5.5)	35.5 (5.9)
Error Ratio	0.45 (0.10)	0.53 (0.10)

Note. [1] The average percentage across 10-runs. [2] The standard deviation across 10-runs.

As seen in Table 2, in the gain condition, there were, on average, 41.6% of A_mA_h combinations and 14.7% of B_mB_h combinations, respectively. In contrast, on average, the erroneous A_mB_h and B_mA_h combinations were 3.3% and 41.4%, respectively. The average error ratio being 0.45. In the loss condition, on average, there were 34.5% of A_mA_h combinations and 13.0% of B_mB_h combinations, respectively.

In contrast, on average, the erroneous A_mB_h and B_mA_h combinations were 17.0% and 35.5%, respectively. The average error ratio being 0.53. Overall, the IBL model with ACT-R default parameters performed poorly compared to the calibrated IBL model.

Figure 2 shows the proportion of A choice (gain condition) or proportion of C choices (loss condition) from human data, IBL model with calibrated parameters, and IBL model with ACT-R default parameters. As can be seen in the Figure, the IBL model with calibrated parameters captured the human choices accurately; whereas, the IBL model with the ACT-R default parameters exhibited a close to a chance performance.

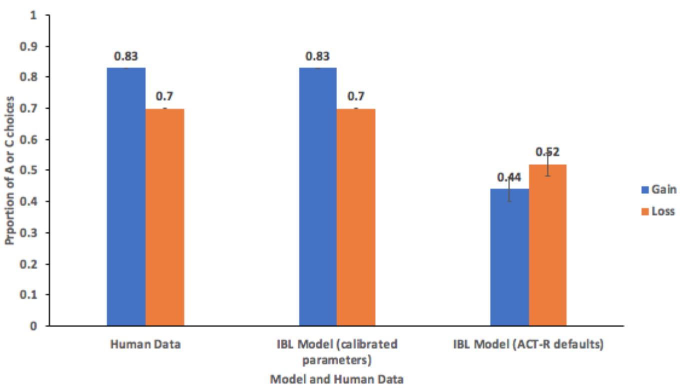

Figure 2. The proportion of A choice (gain condition) or C choices (loss condition) in human data, calibrated IBL model, and IBL model with ACT-R default parameters. The error bars show 95% CI around the average estimate.

Generalization

Since, we first calibrated the IBL model in the gain and loss conditions independently, generalizing the model by running the calibrated parameters in the non-calibrated conditions (from loss condition to gain condition or from gain condition to loss condition) would help account for parameter differences and model consistency across the two conditions. As there was an absence of the framing effect in the experimental data, generalization of loss condition parameters to the gain condition or generalization of gain condition parameters to the loss condition should produce accurate and similar results.

Table 3 shows the results of generalizing the IBL model from calibrated conditions to the non-calibrated conditions. The same results were obtained across 10-runs of the model and there was no deviation in the percentages from the mean. As shown in Table 3, the generalization of loss condition's parameters in the gain condition and the generalization of gain condition's parameters in the loss condition produced most accurate results with 0 error ratios. Thus, these parameters are equivalent and they meet our expectations on the absence of the framing effect in the experienced-based CDP.

Table 3: Generalisation of the calibrated IBL model parameters from calibrated condition to the non-calibrated conditions in CDP.

Human and Model data combination H/M	Loss condition's parameters in gain condition	Gain condition's parameters in loss condition
Parameters	$d = 9.70$, $\sigma = 0.22$	$d = 7.05$, $\sigma = 0.06$
Number of participants	40[1]	40
A_mA_h percentage	83	70
B_mB_h percentage	17	30
A_mB_h percentage	00	00
B_mA_h percentage	00	00
Error Ratio	00	00

Note. [1] Each of the 10-runs of the model produced the same percentage with 0.0 as the standard deviation.

Discussion and Conclusions

Prior research had 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 (Gonzalez et al., 2005; Gonzalez and Mehlhorn 2015; Tversky & Kahneman, 1981). 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. However, little was known about the existence of the framing effect in problems with an applied disease context (e.g., COVID-19) in experience. Also, little was known about how computational cognitive models could account for the framing effect in applied disease contexts in experience. The primary objective of this research was to address these gaps in literature. In this paper, we showed the absence of the framing effect between the gain and loss frames in an applied COVID-19 disease problem (CDP) in experience. Furthermore, we showed that a single IBL model could account for the absence of framing effect in both gain and loss frames in the CDP in experience. The IBL model showed participants relying excessively on recency and frequency of information and showing very little variability in participant-to-participant decisions across both the gain and loss frames in CDP.

First, our experimental results showed an absence of the framing effect across the gain and loss frames in CDP in experience. This result is consistent with those of Gonzalez and Mehlhorn (2015), who also showed the absence of the framing effect across the gain and loss frames in the experience-based ADP. Thus, it seems that the specific COVID-19 disease context (in CDP) is treated by participants in the same manner as the general Asian disease context (in ADP). One likely reason for the absence of the framing effect between gain and loss frames in CDP could be that in experience, people underweight the probability of low frequency events and overweight the probability of the high frequency events (Hertwig & Erev, 2009). Here, this effect of underweighting and overweighting of probabilities seems to be present irrespective of the problem's framing.

Second, our model results showed that the IBL model with calibrated parameters performed exceedingly well compared to the IBL model with ACT-R default parameters. This result extends the work of Gonzalez and Mehlhorn (2015), who developed an IBL model with the ACT-R default parameters. Specifically, it shows that in experience, the default ACT-R assumptions of low recency and reasonable variability may not exist, and people may make more deterministic final choices that are driven by excessive reliance on recent and frequent samples.

Third, our results showed that the generalization of model parameters from calibrated conditions to non-calibrated conditions showed very accurate model performance. This results in particular shows that the IBL model parameters in the gain and loss frames were similar and these parameters tended to agree with the experimental findings on the absence of the framing effect: If there is no preference reversal between gain and loss frames, then the model parameters should also similarity in their values.

There are a number of future directions from this work. First, researchers may also develop the CDP in description and experimentally evaluate whether there is a presence of the framing effect in the description-based CDP. Next, researchers may attempt whether there is an effect of the people's location (being in Asia or in America) on the contextual disease framing in experience and description formats. Furthermore, cognitive models like IBL may be developed on these data to see the potential of such models in capturing the presence or absence of framing effects. In this paper, only base level activation as well as the cognitive noise were used in explaining the framing effect in the IBL model. However, future work may experiment with other ACT-R mechanisms like partial matching or spreading activation to account for these experimental findings. We plan to continue experimenting with some of these ideas as part of our future work in the decisions from experience theme.

Acknowledgments

The authors are grateful to the Indian Institute of Information Technology Una, and Indian Institute of Technology Mandi for providing computational resources for this paper.

References

Anderson, J. R., & Lebiere, C. (1998). *The atomic components of thought*. Hillsdale, NJ: Lawrence Erlbaum Associates. ISBN 0-8058-2817-6

Busemeyer, J. R., & Wang, Y. (2000).Model comparisons and model selections based on the generalization criterion methodology. *Journal of Mathematical Psychology*, 44, 171–189.

Brandstätter, E., Gigerenzer, G., & Hertwig, R. (2006). The priority heuristic: making choices without trade-offs. *Psychological review*, *113*(2), 409.

Dutt, V. and Gonzalez, C. (2012). The role of inertia in modeling decisions from experience with instance-based learning. *Frontiers in Psychology* 3:177. DOI: 10.3389/fpsyg.2012.00177

Erev, I., Glozman, I., & Hertwig, R. (2008). What impacts the impact of rare events. *Journal of Risk Uncertainty* 36:153–177.

Erev, I., Ert, E., Roth, A. E., Haruvy, E., Herzog, S. M., & Hau, R.(2010). A choice prediction competition: Choices from experience and from description. *Journal of Behavioral Decision Mak*ing, 23, 15–47.

Everitt, B. S. (1998). Dictionary of statistics.

Gonzalez, C., Dana, J., Koshino, H., & Just, M. (2005). The framing effect and risky decisions: Examining cognitive functions with fMRI. *Journal of economic psychology*, *26*(1), 1-20.

Gonzalez, C.,& Dutt, V. (2012). Refuting data aggregation arguments and how the instance-based learning model stands criticism: A reply to Hills and Hertwig *Psychological Review*, *Vol* 119(4),893-898.

Gonzalez, C., & Dutt, V. (2011). Instance-Based Learning: Integrating Sampling and Repeated Decisions From Experience. *Psychological Review*,118(4), 523-551.

Gonzalez, C., & Mehlhorn, K. (2015). Framing From Experience: Cognitive Processes and Predictions of Risky Choice. *Cognitive Science*, *1*, 29. DOI: 10.1111/cogs.12268

Hertwig, R., & Erev, I. (2009). The description-experience gap in risky choice. *Trends in Cognitive Sciences*, 13, 517-523.

Hertwig, R., & Pleskac, T. J. (2010). Decisions from experience: Why small samples*?. Cognition*, 115,225–237.

Hertwig, R. (2012). The psychology and rationality of decisions from experience. *Synthese*, 187, 269-292.

Lebiere, C. (1999). Blending: An ACT–R mechanism for Aggregate retrievals. *Paper presented at the 6th Annual ACT–R Workshop at George Mason University*. Fairfax County, VA.

Lejarraga, T. & Dutt, V. & Gonzalez, C. (2012). Instance-Based Learning: A general model of repeated binary choice. *Journal of Behavioral Decision Making*,25: 143-153.

PGI to test leprosy vaccine on Covid-19 patients(2020, Apr 22) Retrieved from https://www.hindustantimes.com/chandigarh/pgi-to-test-leprosy-vaccine-on-covid-19-patients/story-0DHH4GS8mANbUZNRZj2kYK.html

Rieskamp, J. (2008). The probabilistic nature of preferential choice. Journal of Experimental Psychology: Learning, Memory, and Cognition, 34(6), 1446.

Sharma, N., & Dutt, V. (2017). Modeling decisions from experience: How models with a set of parameters for aggregate choices explain individual choices. *Journal of Dynamic Decision Making*, *3*, 3-3.

Sharma, N., Debnath, S., & Dutt, V. (2018). Influence of an Intermediate Option on the Description-Experience Gap

and Information Search. *Frontiers in psychology*, *9*, 364.
Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology ofchoice. *science*, *211*(4481), 453-458.
Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*,*5* (4), 297-323.