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Life and Death Decisions and COVID-19: Investigating and Modeling the Effect of Framing, Experience, and Context on Preference Reversals in the Asian Disease Problem

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Abstract

Prior research in judgment and decision making (JDM) has investigated the effect of problem framing on human preferences. Furthermore, research in JDM documented the absence of such reversal of preferences when making decisions from experience. However, little is known about the effect of context on preferences under the combined influence of problem framing and problem format. Also, little is known about how cognitive models would account for human choices in different problem frames and types (general/specific) in the experience format. One of the primary objectives of this research is to investigate the presence of preference reversals under the influence of problem framing (gain/loss), problem format (experience/description), and problem type (general/specific). Another objective of this research is to develop cognitive models to account for human choices across different problem frames and types in the experience format. A total of 320 participants from India were randomly assigned to one of eight between-subjects conditions that differed in problem frame, format, and type. Results revealed preference reversals in the description condition; however, they were absent in the experience condition. Moreover, preference reversals were less pronounced in the general problem framing

compared to the specific problem framing. Furthermore, specific problems influenced risk-seeking behavior among participants. We developed cognitive and heuristics models using instance-based learning theory and natural mean heuristic. Results reveal models' dependency on recent and frequent observations during information sampling. These experience-based cognitive models could help build artificial intelligence models with fewer preference reversals.

Keywords: Framing effect; COVID-19; Asian disease problem; Decisions from experience; Preference reversals; Instance-based learning

1. Introduction

Preference reversals are systematic inconsistencies between preferences and associated utility (Grether & Plott, 1979; Lichtenstein & Slovic, 1971, 1973; Tversky, Slovic, & Kahneman, 2006) and hard to replicate using exiting artificial intelligence techniques. Several theories have been proposed to explain the reversal of preferences at different stages during the decision-making process. These theories explain how preference reversals can cause changes in how options are weighted (Sharma & Dutt, 2017; Tversky, Slovic, & Kahneman, 1990), how evaluations are made by combining the weighted options (Mellers, Weiss, & Birnbaum, 1992), or how these evaluations are expressed in different problems (Goldstein & Einhorn, 1987).

One example of preference reversal is the framing effect (Tversky & Kahneman, 1981), studied using different problem frames involving the famous Asian disease problem (ADP). In ADP, participants are asked to imagine that there has been an outbreak of an unusual Asian disease in their country, which is expected to kill 600 people (Tversky & Kahneman, 1981). Participants are tasked to choose a health program out of the two available programs to save the people's lives (one of the programs provides a safe choice and the other program provides a risky choice). One group of people is presented with a gain problem frame regarding "lives saved." In contrast, the second group of people has the same problem with a loss problem frame regarding "lives lost." While both the problem frames are equivalent in expectation of their outcomes, results reveal a reversal in preference of option chosen in majority by the two groups (Gonzalez & Mehlhorn, 2016; Tversky & Kahneman, 1981). The safe option is selected by most people presented with the gain frame; whereas, the risky option is chosen by many people presented with the loss frame (Gonzalez & Mehlhorn, 2016; Tversky & Kahneman, 1981).

Research in human cognition has also found preference reversals when people make decisions from different formats: description or experience (Dutt & Gonzalez, 2012a; Erev et al., 2010; Gigerenzer & Gaissmaier, 2011; Hertwig & Erev, 2009; Hertwig, Barron, Weber, & Erev, 2004; Lejarraga, Dutt, & Gonzalez, 2012; Lieder, Griffiths, Huys, Q., & Goodman, 2018; Sharma & Dutt, 2017). In the description format, people are presented with textual descriptions of options containing consequences and likelihoods (Hertwig & Erev, 2009; Sharma & Dutt, 2017; Tversky & Kahneman, 1992). In the experience format, people are provided with the ability to search options, where they learn about the consequences

contained with certain frequency or probability governing the consequences (Gonzalez & Mehlhorn, 2016; Hertwig & Erev, 2009; Hertwig et al., 2004; Sharma & Dutt, 2017). Once people are satisfied with their searching for options, they make a final consequential choice for real. Although the description and experience formats may seem similar, they produce preference reversals: people tend to underweight the low probabilities in experience and overweight them in description (Dutt & Gonzalez, 2012a; Erev, Ert, & Yechiam, 2008; Hertwig et al., 2004; Wulff, Hills, & Hertwig, 2015). The underlying cognitive mechanisms supporting this finding include reliance on recency and frequency of sampled informa- tion and cognitive inertia (Gonzalez & Dutt, 2011; Gonzalez & Dutt, 2012; Sharma & Dutt, 2017).

Prior research also indicates that the problem context or type (general or specific) may play a role in influencing people's preferences. In the Dutt and Gonzalez (2013) investigation, participants presented with a climate context were less responsive than those presented with a marble context. The participants were asked to graphically represent the inflow and outflow of CO_2 emissions in the atmosphere over 5 years in the climate context. In the marble context, participants were asked to graphically represent the number of marbles inserted in (inflow) and removed out (outflow) of the container. It was observed that par- ticipants assigned to climate context were less responsive in graphically representing the inflow and outflow of CO_2 emissions compared to the participants who were given the marble context. Similarly, in a study on framing investment options, Sharma, Debnath, and Dutt (2018) found that a description-experience gap was absent when the experiment was presented without investment framing. Furthermore, Wulff et al. (2015) showed that products with familiar contexts receive more ratings on e-commerce portals than unfamiliar ones.

Although prior research has investigated the effect of different contexts on participant's performance (Dutt & Gonzalez, 2013), investment behavior (Sharma et al., 2018), and product rating on e-commerce websites (Wulff et al., 2015), little is known about how general and specific contexts would affect the human preferences under risk under the combined influence of different problem frames and problem formats.

Cognitive models have also been developed to account for human choices in different prob- lem frames in the experience format (Gonzalez & Mehlhorn, 2016; Sharma, Uttrani, & Dutt, 2020; Uttrani, Sharma, & Dutt, 2020). For example, Gonzalez and Mehlhorn (2016) presented their instance-based learning (IBL) model with default ACT-R (Anderson, 2007; Anderson & Lebiere, 1998; Bothell, 2008; Ritter, Tehranchi, & Oury, 2019) parameters to model the absence of framing effect across gain and loss conditions in the experience format of the ADP. However, Gonzalez and Mehlhorn (2016) did not calibrate the model's parameters to account for human choices. Also, Gonzalez and Mehlhorn (2016) did not discuss how cognitive models like IBL would account for human choices driven by different contexts. Later, Sharma et al. (2020) and Uttrani et al. (2020) developed and calibrated IBL models for context-specific problems, such as Coronavirus disease. However, the authors did not com- pare their models to an abstract problem. Moreover, IBL models and heuristic rules were not compared when accounting for human choices.

The primary objectives of this research are twofold. First, we aim to investigate the effect of context or problem type (general or specific) on decisions under the influence of problem frame (gain or loss) and problem format (description or experience). In the gain frame, options are presented positively; whereas, in the loss frame, the options are presented in a negative connotation. In problem format, outcomes and probabilities are either described as a written text, or outcomes are experienced with the underlying frequency upon a search. In the general problem type, an abstract problem description of an ADP is provided (absence of context); whereas, in the specific problem type, a specific description of the COVID-19 disease problem (CDP) is provided (presence of context). Next, we develop and calibrate cognitive models using instance-based learning theory (IBLT) (Gonzalez & Dutt, 2011; Gonzalez, Lerch, & Lebiere, 2003) and natural mean heuristic (NMH) (Hertwig & Pleskac, 2010) for explaining human choices in different problem types across the gain and loss problem frames in the experience format. This research would help provide theoretical and practical advancements in understanding preference reversals due to problem frames, format, and types. Such an investigation would allow the cognitive science and AI community to understand the underlying reasons for the absence of preference reversal in experience formats based on information sampling.

In what follows, first, we recap the literature on decision making under the influence of problem framing, format, and type. Next, we present a laboratory experiment involving human participants, who are tasked to make decisions related to health programs during a disease outbreak. Next, cognitive models and heuristics are developed using IBLT and NMH to explain human decisions obtained in the laboratory experiment. Finally, we close the paper by discussing the implications of our results for the cognitive science and artificial intelligence (AI) community.

2. Background

Prior research in judgment and decision making (JDM) has documented the differences in human decisions in different problem types, that is, when decisions are made in the presence of general or specific problem types (Bless, Betsch, & Franzen, 1998; Gonzalez et al., 2003; Lieder & Griffiths, 2017; Vlaev, Kusev, Stewart, Aldrovandi, & Chater, 2010; Wulff et al., 2015). In the general type, people are presented with an abstract problem and different alternatives to make a final choice. Similarly, people are presented with a context-based problem and different alternatives in the specific type. Results show that people are less responsive when presented with a general problem in making consequential decisions. However, when presented with a context-based problem, people are more responsive in making consequential decisions (Brunstein, Gonzalez, & Kanter, 2010; Gigerenzer & Hug, 1992; Sharma et al., 2018; Tversky & Simonson, 1993; Wulff et al., 2015). This human behavior has been attributed to unfamiliarity with the situation (Ludvig, Sutton, & Kehoe, 2012; Tversky & Simonson, 1993; Wulff et al., 2015). In the specific type, the context seems to provide a familiarity with the problem presented to the people, which helps nudge their behavior from

being less responsive to more responsive in decision making. Therefore, we expect people to show risk-seeking behavior in specific problems compared to general problems across decision choices.

Furthermore, previous research in JDM has also documented the joint effect of problem framing and problem type on people's consequential decisions (Bless et al., 1998; Gonzalez et al., 2003; Lieder & Griffiths, 2017; Vlaev et al., 2010; Wulff et al., 2015). Results show no change in people's preferences across general and specific problems in the gain frame (Bless et al., 1998; Gonzalez et al., 2003; Lieder & Griffiths, 2017; Vlaev et al., 2010; Wulff et al., 2015). However, in the loss frame, a large majority of people tend to choose the risky option when presented with a specific problem compared to a general problem (Bless et al., 1998; Gonzalez et al., 2003; Lieder & Griffiths, 2017; Vlaev et al., 2010; Wulff et al., 2015). Therefore, we expect more people to show risk-seeking behavior in specific problems than general problems across decision choices in the loss condition compared to the gain condition.

Although there has been work about the main effects of problem format and problem type; however, little is known about the joint effect of problem format and problem type on people's preferences. According to the literature on problem format, people underweight the probability of low-frequency events in the experience format; whereas, people overweight the probability of low-probability events in description format (Gonzalez & Dutt, 2011; Hau, Pleskac, Kiefer, & Hertwig, 2008; Hertwig, 2012; Hertwig & Erev, 2009; Hertwig et al., 2004; Sharma et al., 2018; Weber, Shafir, & Blais, 2004). Similarly, according to the literature on problem type, people tend to avoid risky options when the general problem is presented. However, in specific problems, people show risk-seeking behavior (Bless et al., 1998; Gonzalez et al., 2003; Lieder & Griffiths, 2017; Vlaev et al., 2010; Wulff et al., 2015). Overall, we expect people to underweight risky options in specific problems in the experience format; whereas, overweight risky options in the specific problem in the description format.

Research in decisions from experience has largely investigated the importance of information sampling in the decision-making process (Gonzalez & Dutt, 2011; Hertwig et al., 2004). Hertwig et al. (2004) experimentally showed that people rely on recently sampled information for making decisions against rare events. IBLT (Gonzalez & Dutt, 2011; Gonzalez et al., 2003) proposes that experiences, in the form of "instances," are stored and retrieved from memory by people to make decisions. In IBLT, an instance is defined as a triplet structure consisting of a situation, a decision, and a utility stored in the memory, generated from different experiences during a decision task. Similarly, according to the NMH (Hertwig & Pleskac, 2010), sample size, frequency of the outcomes, and the associated utility influence people's choices during decision-making tasks. Overall, first, we expect that the IBL model with calibrated parameters (IBL calibrated) will perform better than the IBL model with default ACT-R parameters (IBL ACTR) and the NMH model. Second, we expect that the IBL (calibrated) will give more weight to the recent outcomes than the IBL (ACTR) while accounting for human choices in the experience format. Third, we expect that the reliance on recency of outcomes in case of specific problems (rare occurrences) will be higher than general problems (frequent occurrences).

3. Experiment

This section details an experiment to evaluate the presence or absence of preference reversals related across different problem framings, formats, and types.

3.1. Participants

This study was carried out following the Ethics Committee's recommendations at the Indian Institute of Technology Mandi with written consent from all participants. A total of 320 participants were recruited from India to participate in the study through Amazon Mechanical-Turk (Crump, McDonnell, & Gureckis, 2013; Paolacci & Chandler, 2014). Participation in the study was voluntary, and about 76% of participants were males, and the rest were females. Ages ranged from 18 to 50 years (mean = 29 years and standard deviation = 5.7 years). Participants were from different education levels: 6% undergraduates, 93% graduates, and 1% postgraduates. The demographics were the following: 56% possessed degrees in science, technology, engineering, and management, and 40% had degrees in humanities and social sciences. Participants were compensated INR 21 ($\sim$ USD 0.28) for their participation in the study. No participant took more than 10 min to complete the study.

3.2. Experiment design

Participants were randomly assigned to eight between-subjects conditions ($N = 40$ in each condition) across different problem frames, formats, and types: Description-ADP-Gain, Description-ADP-Loss, Description-CDP-Gain, Description-CDP-Loss, Experience-ADP-Gain, Experience-ADP-Loss, Experience-CDP-Gain, and Experience-CDP-Loss. In all the description conditions, participants had to read about a given problem (either ADP or CDP) and decide to choose one of the presented health programs (A or B) by clicking the button corresponding to the program.

In all description conditions, the probability and outcome (lives saved or lives lost) information in the two health programs (A and B) was available to participants while making their decisions. In all the experience conditions, participants were given a problem statement and two programs, A and B, as two button options. First, participants were asked to search the option buttons by clicking upon them. Participants could search the buttons as many times and in any order they desired before making a final consequential choice. Clicking an option button caused the outcomes to be revealed to participants. These outcomes on option buttons occurred with a predefined probability distribution. The searching of buttons in all experience conditions was nonconsequential (thus, the outcome revealed during the search did not influence participants' payoffs). During the search, participants could click the "Make Allocation for Real" button at any time. Upon clicking the "Make Allocation for Real" button, the search was terminated, and participants moved to make a consequential choice. Next, participants were asked to make a consequential choice for one of the programs. Clicking a program button in experience conditions during the search or consequential choice revealed

the outcome to participants only. Thus, the probability information associated with outcomes was not revealed.

The problem type was either general (ADP) or specific (CDP). In ADP, the problem was presented as, "There is an outbreak of an unusual Asian disease in your country." Whereas, in the CDP, the problem was presented as, "There is an outbreak of the coronavirus disease in your country."

In all the gain conditions, program A was framed as "200 people will be saved" (having probability = 1), and program B was framed as "600 people will be saved" (having probability = 1/3) or "No one will be saved" (having probability = 2/3). On the contrary, in all the loss conditions, program C was framed as "400 people will die" (having probability = 1), and program D was framed as "Nobody will die" (having probability = 1/3) or "600 people will die" (having probability = 2/3). Across both gain and loss conditions, it can be observed that programs A and C were identical, and programs B and D were identical.

3.3. Stimuli

The study began with an instruction page where the general instructions related to the experiments were described in detail for the description (Fig. 1a) and the experience format (Fig. 1b). Upon clicking the "Continue" button on the instruction page, the participants were redirected to the experiment page to make their final consequential choice in description format or sample the information in the experience format. Fig. 2a shows the interface shown to participants in the Description-ADP-Gain condition of the study. As shown in Fig. 2a, participants were presented with the descriptive format of the ADP in the gain frame. Participants had to choose between the two available health programs, program A and program B, by clicking on the respective program buttons. Similarly, participants assigned to the Description-CDP-Loss condition (Fig. 2b) were presented with the descriptive format of the CDP in the loss frame. Participants assigned to the Experience-ADP-Gain condition (Fig. 3a) were presented with the experiential format of the ADP in the gain frame. Finally, participants assigned to the Experience-CDP-Loss condition (Fig. 3b) were presented with the experiential format of the CDP in the loss frame.

3.4. Procedure

Participants were randomly assigned to one of eight between-subject conditions via a weblink on the Amazon Mechanical Turk portal. First, participants were presented with a consent form. After consent, they were presented with instructions. Participants provided with the descriptive format in the gain (or loss) conditions were asked to provide their final consequential choice after reading the problem immediately. In contrast, participants presented with the experience format were initially asked to search the available option as many times and in any order they preferred before making a final choice. Once participants completed their study, they were thanked and paid for their participation.
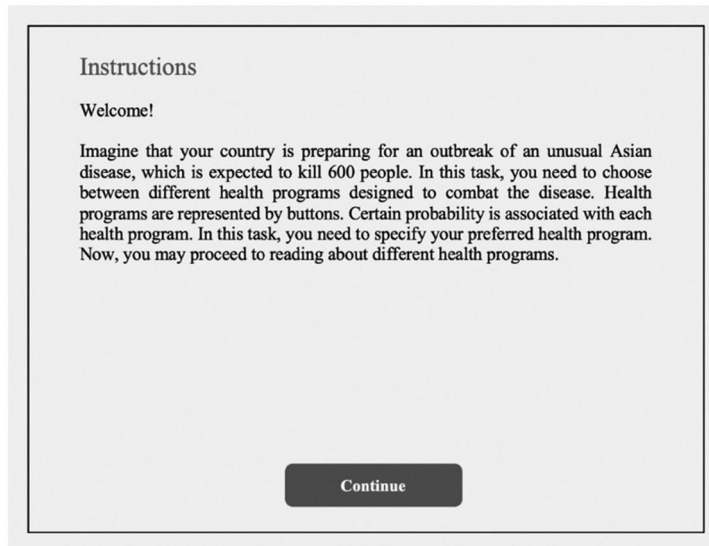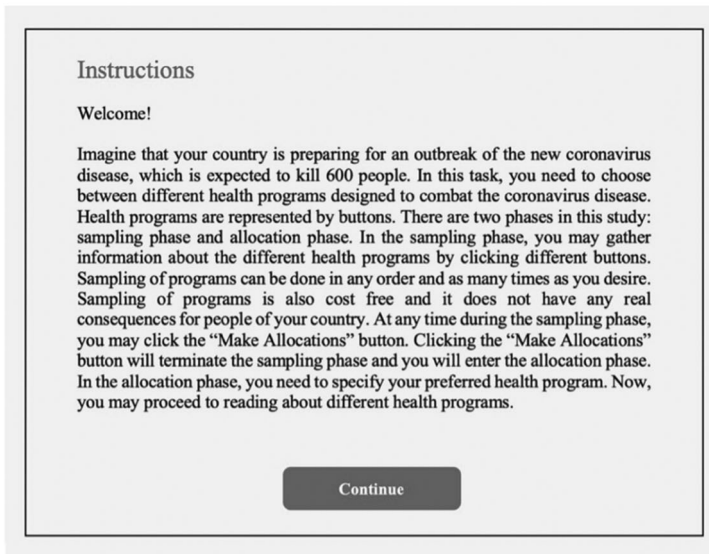
Fig. 1. The instruction page for (a) the Asian disease problem (ADP) in description format and (b) the Coronavirus disease problem (CDP) in the experience format.

3.5. Data analyses

For analyzing data, we checked different assumptions and performed a three-way ANOVA (Field, 2013) to investigate the influence of three independent variables, that is, framing,

Fig. 2. The ADP problem in the gain frame (a) and the CDP problem in loss frame (b) in the description format.

format, and type, on a participant's final decision. The alpha level was set at 0.05. The power was set at 0.80. The dependent variable, that is, the proportion of safe (program A or C) choices in all conditions, was evaluated. Problem framing included gain and loss frames, problem format included description and experience, and problem type included general and

Fig. 3. The Asian disease problem (ADP) in the gain frame (a) and the Coronavirus disease problem (CDP) in the loss frame (b) in the experience format.

specific problems. The dependent variable was found to be normally distributed based on the Q-Q plots (between expected quantiles and normal quantiles). Furthermore, the dependent variable was found to have homogeneous variances based upon the visualizations of the scatter plots of the dependent variable across conditions.
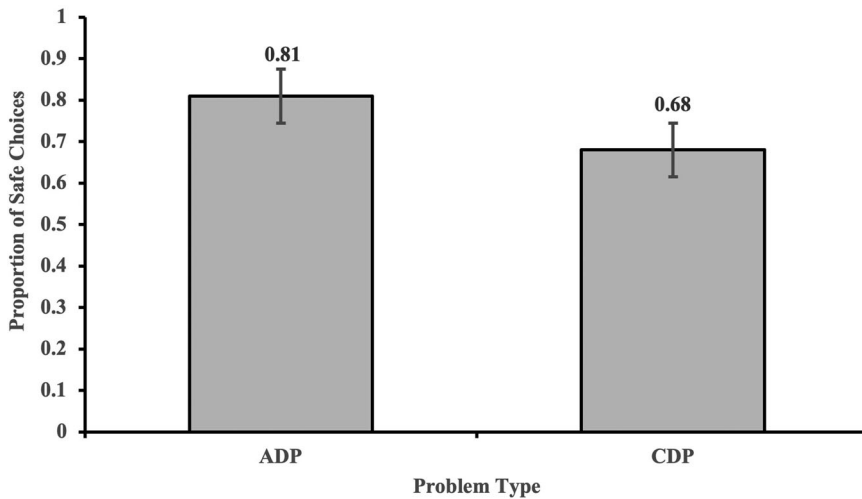
Fig. 4. The proportion of safe choices across Asian disease problem (ADP) and Coronavirus disease problem (CDP). The error bars show 95% CI around the average estimate.

4. Experimental results

We performed a three-way analysis of variance to investigate the influence of problem type on decisions made by participants.

4.1. Influence of problem type on decisions

Following the problem framing and format, the problem type also significantly influenced the proportion of safe choices ($F (1,312) = 9.2$, $p = .003$, $\eta^2 = 0.026$). Thus, as shown in Fig. 4, the proportion of safe choices was 0.81 in the ADP; however, the proportion of safe choices was 0.68 in the CDP. Therefore, our expectations of people showing risk-seeking behavior in specific problems compared to general problems have been met.

4.2. Influence of problem frame and type on decisions

The two-way interaction effect between problem frame and type was also significant ($F (1,312) = 6.3$, $p = .013$, $\eta^2 = 0.018$). This result indicated the influence of both problem frame and type on the proportion of safe choices (Fig. 5). The post-hoc tests revealed that the proportion of safe choices in ADP was significantly greater than CDP for loss frame ($p < .001$). However, there was no difference between the proportion of safe choices in ADP compared to CDP for the gain frame ($p = .67$). According to these results, we can say that the difference in the proportion of safe choices between decisions made in the presence of a general context and a specific context will be greater when the problem is presented in the loss frame than in the gain frame.
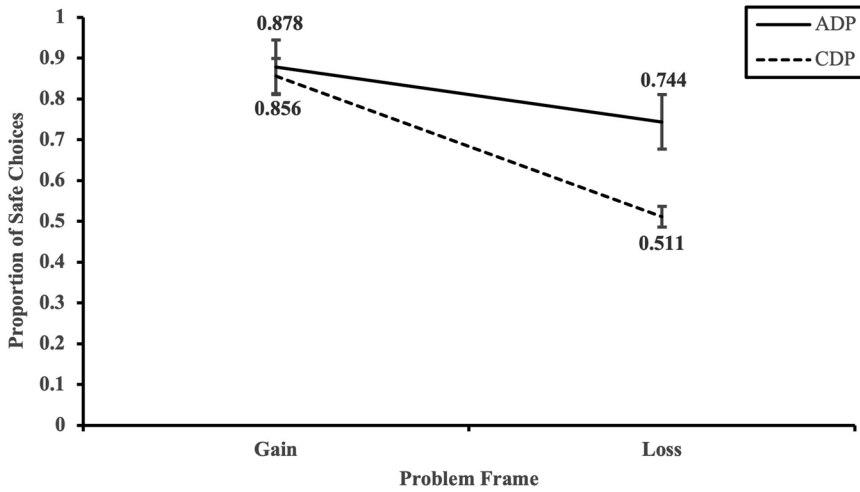
Fig. 5. The proportion of safe choices made in gain and loss problem frames across ADP and CDP problem types. The error bars show 95% CI around the average estimate.
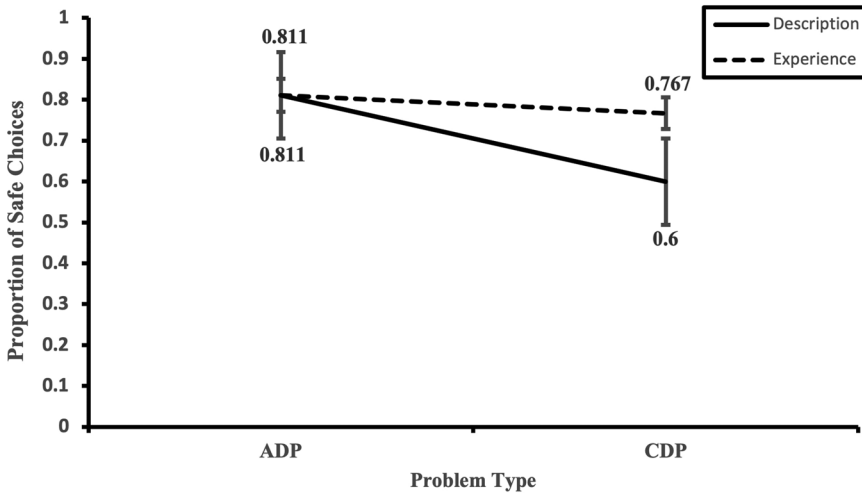
Fig. 6. The proportion of safe choices made in Asian disease problem (ADP) and Coronavirus disease problem (CDP) types across description and experience problem format. The error bars show 95% CI around the average estimate.

4.3. Influence of problem type and format on decisions

The two-way interaction between problem type and format was also significant ($F (1,312) = 3.9$, $p < .05$, $\eta^2 = 0.011$). This result indicated the influence of both problem type and format on the proportion of safe choices (Fig. 6). The post-hoc tests revealed that the proportion of safe choices in the experience format was significantly greater compared

to the description format for CDP ($p = .016$). However, there was no difference between the proportion of safe choices in description format compared to experience format for ADP ($p > .05$). These results are as per expectations that people underweight risky options in specific problems in the experience format, whereas overweight risky options in the specific problem in the description format.

4.4. Influence of problem type, format, and frame on decisions

The three-way interaction between problem framing, type, and format was not significant ($F(1,312) = 2.1$, $p = .147$, $\eta^2 = 0.006$). Thus, the nature of effects between problem format and problem frame was similar across both the problem types.

5. Models

In this section, we explain the working of an IBL model and an NMH model developed to account for human choices in different problem frames and problem types in the experience format.

5.1. IBL model

In an IBL model (Gonzalez & Dutt, 2011; Gonzalez et al., 2003), the outcomes observed during the sampling phase are stored in memory in the form of instances. The activation of these instances is a function of the frequency and recency of the observed outcomes. The availability of these stored instances decays over time, and, therefore, the more recent and frequent outcomes will highly influence the final choice made by the model. To make the final decision from the available options, the IBL model calculates the blended value for each option, which depends on each outcome's likelihood, also known as the probability of retrieval of an instance from memory in the IBL theory. The evaluation of blended values is like calculating expected values, given a set of probabilities for each option and associated values.

The two free parameters of the IBL model that need to be calibrated are d and σ. The d parameter controls the reliance on recent or distant sampled information. Thus, when d is large (> 1.0), 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. Sampling done by the individual human participants is fed to generate instances in memory. During sampling, each time a choice is made, and the outcome is observed, an instance associated with the outcome is activated (created or reinforced if already present). 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 (ACTR), the ACT-R parameters' default values were used, that is, $d = 0.50$ and $\sigma = 0.25$, where ACT-R is a cognitive architecture developed to account for human decisions (Anderson, 2007; Anderson & Lebiere, 1998; Bothell, 2008;

Ritter et al., 2019). These ACT-R parameters show lesser reliance on recency and frequency of the information and a reasonable participant-to-participant variability in final choices. In another version of the IBL model, single values of the two parameters (d and σ) were found by calibrating them to individual participant final choices. This latter model is referred to as the IBL (calibrated). One of the limitations of using the IBL model to account for human choices is that the IBL model is insensitive to problem framing and type. Neither the problem framing nor the problem type is included in the model. However, recalibrating the model's parameters between different problem frames and types acts as a proxy mechanism to account for human choices across gain versus loss problem frames and general versus specific problem types. For this model's parameter calibration, a model participant's choice was determined and compared to a human participant's choice. The model's memory in the calibrated and ACT-R model was prepopulated with two instances (i.e., one on each option) with a 1000 utility to create an exploration of options during sampling. The utility value was kept higher than all possible outcomes in different options. These prepopulated instances represent the initial expectations participants may bring to the task (Gonzalez & Dutt, 2011). The dependent variable (error) was coded as zero if the model participant's choice equaled the human participant's choice; otherwise, the error was coded as one. The average errors across all participants were minimized in the IBL (calibrated). The mathematical formulation of the IBL model and its calibration methodology have been reported in several past publications (Gonzalez & Dutt, 2011; Gonzalez et al., 2003; Sharma & Dutt, 2017).

5.2. NMH model

The final choice made by humans in the experience format is influenced by the sample size, the frequency of observed outcomes, and the utility associated with those experienced outcomes (Dutt & Gonzalez, 2012b; Gonzalez & Dutt, 2011, 2012; Hertwig & Erev, 2009). To account for all these effects, the NMH model is developed, which first computes the natural mean of the observed outcomes during sampling of different options and then makes a final decision by choosing the option with the highest mean (Hertwig & Pleskac, 2010). Similar to the IBL, NMH model is also insensitive to problem frame and type. This comes as a limitation of NMH model to account for human choices across different experimental conditions, such as problem frames and types. Moreover, NMH being a parameter-free model, recalibration of NMH model across gain versus loss problem frames and general versus specific problem type.

5.3. Dependent variables and Akaike information criterion calculation

We evaluated an error ratio (the ratio of incorrectly classified final choices between model and human participants divided by the total number of human participants) to compare human and model choices for each model. Thus, the error ratio was calculated as:

$$Error\ Ratio\ =\ (A_m B_h + B_m A_h)\,/\,(A_m A_h + B_m B_h + A_m B_h + B_m A_h)\,, \qquad (1)$$

where, $A_m B_h$ 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. $B_m A_h$ was the number of participants where the model predicted a B (or D) program choice, but the human participant made an A (or C) program choice. Similarly, the $A_m A_h$ and $B_m B_h$ 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 the model is in accounting for individual consequential choices.

We calculated the Akaike information criterion (AIC) (Akaike, 1974) value to evaluate and compare the performance of all three models. AIC, for model selection, estimates the quality of each model on a given dataset relative to other models. The estimation is performed by calculating the relative amount of information lost by a given model, that is, the less information lost by a model, the better the quality of that model. The AIC value of a model was calculated as:

$$AIC \,=\, t * \ln \frac{SSE}{t} + 2 * k \qquad (2)$$

$$SSE \,=\, \sum_{i=1}^{t} \left(x_{model,\ i} - x_{human,\ i} \right)^2 ,$$

where, $x_{model,i}$ and $x_{human,i}$ are the average dependent measures in the model data and human data over t trials. The dependent measure's average has been calculated over all participants. The sum of squared errors (SSE) between human and model data is calculated for the average dependent measure. The number of trials within a task is represented by t and k denotes the number of free parameters in a model. The effect of mean square deviation and the number of parameters are incorporated by the AIC. Smaller or more negative values of AIC signify the better performance of a model than others.

5.4. Model execution

The number of simulations was set such that the models produced a stable result with a small standard deviation every time they were run across participants (Ritter, Schoelles, Quigley, & Klein, 2011). In both the gain and loss conditions of the ADP and CDP problem types, the IBL (calibrated) was run for 10 simulations, where each simulation consisted of 40 model participants. For a model participant, the model first sampled the available options in the same manner as done by the corresponding human participant (sampling phase). Thus, in the sampling phase, the model created instances in its memory of the form: (two buttons [situation], the button sampled [decision], the outcome obtained [utility]). If the outcome obtained was the same as that in an instance in the memory upon sampling a button, then the instance's activation was reinforced. Once the sampling phase was over, the model computed the probability of retrieval of instances and the blended value corresponding to each choice decision (the task required choosing between two choice buttons). The model in the task executed the decision with the higher blended value.

Table 1

Results of IBL (calibrated), IBL (ACTR), and NMH model across gain and loss frames in ADP

Human and model data combination H/M	IBL (calibrated)		IBL (ACTR)		NMH model	
	Gain condition	Loss condition	Gain condition	Loss condition	Gain condition	Loss condition
Parameters	$d = 7.39$, $\sigma = 0.11$	$d = 8.90$, $\sigma = 0.12$	$d = 0.50$, $\sigma = 0.25$	$d = 0.50$, $\sigma = 0.25$	No free parameters	No free parameters
No. of participants	40	40	40	40	40	40
$A_m A_h$ %	83[a] (0.0)[b]	83 (0.0)	43 (5.9)	33 (4.8)	70 (0.0)	20 (0.0)
$B_m B_h$ %	17 (0.0)	17 (0.0)	10 (3.1)	15 (2.7)	17.5 (0.0)	17.5 (0.0)
$A_m B_h$ %	0 (0.0)	0 (0.0)	7 (3.2)	2 (2.6)	0 (0.0)	5 (0.0)
$B_m A_h$ %	0 (0.0)	0 (0.0)	40 (6.0)	50 (4.7)	12.5 (0.0)	57.5 (0.0)
Error ratio	0.00 (0.0)	0.00 (0.0)	0.48 (0.10)	0.53 (0.10)	0.13 (0.0)	0.63 (0.0)

Similarly, the IBL (ACTR) was also run for 10 simulations in both the gain and loss conditions of the ADP and CDP problem types. Again, each of the 10 simulations consisted of 40 model participants. Each model participant in the IBL (ACTR) was run using the same procedure as described above for the IBL (calibrated). As there was no variability present in the NMH model, it was run for only one simulation of 40 model participants in both the gain and loss conditions of the ADP and CDP problem types.

The two free parameters of the IBL (calibrated) were calibrated, using a genetic algorithm (GA) that we created, in both the gain and loss conditions of the ADP and CDP problem types. The values of d and σ parameters were both varied in the range [0, 10]. A tuple of d and σ parameters corresponding to the minimum error ratio was found by repeatedly modifying a population of individual parameters in the GA program. For the IBL (ACTR), the default values of d (= 0.5) and σ (= 0.25) were used to run the model for 40 model participants across 10 simulations. The NMH model did not require any parameter calibration as there were no free parameters.

6. Model results

The IBL (calibrated) was able to account for human choice accurately, reporting zero error ratio across gain and loss conditions in ADP (Table 1) as well as CDP (Table 2). However, the IBL (ACTR) reported an average error ratio of 0.48 in the gain condition and 0.53 in the loss condition in ADP. Similarly, in CDP, the average error ratio reported by the IBL (ACTR) was 0.45 and 0.53 for gain and loss conditions, respectively. The NMH model, in ADP, reported an average error ratio of 0.13 in the gain condition and 0.63 in the loss condition. Similarly, in CDP, the NMH model reported an error ratio of 0.18 in the gain condition and 0.55 in the loss condition. Overall, the IBL (calibrated) performed the best among all three models. These results are per our expectations that the IBL (calibrated) gives more weight to the recent and frequent observations than the IBL (ACTR).

Table 2
Results of IBL (calibrated), IBL (ACTR), and NMH model across gain and loss frames in CDP

Human and model data combination H/M	IBL (calibrated)		IBL (ACTR)		NMH model	
	Gain condition	Loss condition	Gain condition	Loss condition	Gain condition	Loss condition
Parameters	$d = 7.05, \sigma = 0.06$	$d = 9.70, \sigma = 0.22$	$d = 0.50, \sigma = 0.25$	$d = 0.50, \sigma = 0.25$	No free parameters	No free parameters
No. of participants	40	40	40	40	40	40
$A_m A_h$ %	83[a] (0.0)[b]	70 (0.0)	41.6 (5.5)	34.5 (5.9)	65 (0.0)	22.5 (0.0)
$B_m B_h$ %	17 (0.0)	30 (0.0)	14.7 (3.0)	13 (2.6)	17.5 (0.0)	22.5 (0.0)
$A_m B_h$ %	0 (0.0)	0 (0.0)	3.3 (3.0)	17 (2.6)	0 (0.0)	7.5 (0.0)
$B_m A_h$ %	0 (0.0)	0 (0.0)	41.4 (5.5)	35.5 (5.9)	17.5 (0.0)	47.5 (0.0)
Error ratio	0.00 (0.0)	0.00 (0.0)	0.45 (0.0)	0.53 (0.10)	0.18 (0.0)	0.55 (0.0)

[a]The average percentage across 10 runs.
[b]The standard deviation across 10 runs.

To account for the individual consequential choices, we evaluated the IBL model's ability in both gain and loss conditions separately across both problem types, that is, ADP and CDP. In the gain condition of ADP, the best-calibrated values of d and σ were found to be 7.39 and 0.11, respectively. In the loss condition of ADP, the best-calibrated values of d and σ were found to be 8.90 and 0.12, respectively. Similarly, in the gain condition of CDP, the best-calibrated values of d and σ were found to be 7.05 and 0.06, respectively. In the loss condition of CDP, the best-calibrated values of d and σ were found to be 9.70 and 0.22, respectively. The high values of d showed the model's reliance on recency during sampling, and the low σ value showed lesser participant-to-participant variability in instance activations. The IBL (calibrated) possessed higher values d and σ in CDP compared to ADP in the loss frame; however, in the gain frame, these values were equivalent in ADP and CDP. Thus, our expectation of the IBL (calibrated) performing better than the IBL (ACTR) and the NMH model is met. Our expectation of the IBL (calibrated) giving more weight to the recent outcomes and exhibiting lesser variance in participant-to-participant instance activation than the IBL (ACTR) is also met. Furthermore, our expectation of reliance on recency of outcomes in case of specific problems (rare occurrences) to be higher compared to general problems (frequent occurrences) is also met.

The individual-level results obtained from the gain and loss conditions for ADP and CDP are shown in Tables 1 and 2, respectively. The IBL (calibrated) and the NMH model produced the same results across 10 runs, and there was no deviation in the mean percentages across both problem formats. For the IBL (ACTR), the average percentages across 10 runs and their respective standard deviations are shown in Tables 1 and 2 for ADP and CDP, respectively.

Figs. 7 and 8 show the proportion of safe choices (i.e., program A) in gain condition or the proportion of safe choices (i.e., program C) in loss condition from human data, the IBL (calibrated), the IBL (ACTR), and the NMH model in the ADP and CDP problem types, respectively. The IBL (calibrated) captured human choices perfectly, whereas the IBL (ACTR) and the NMH model did not perform well.
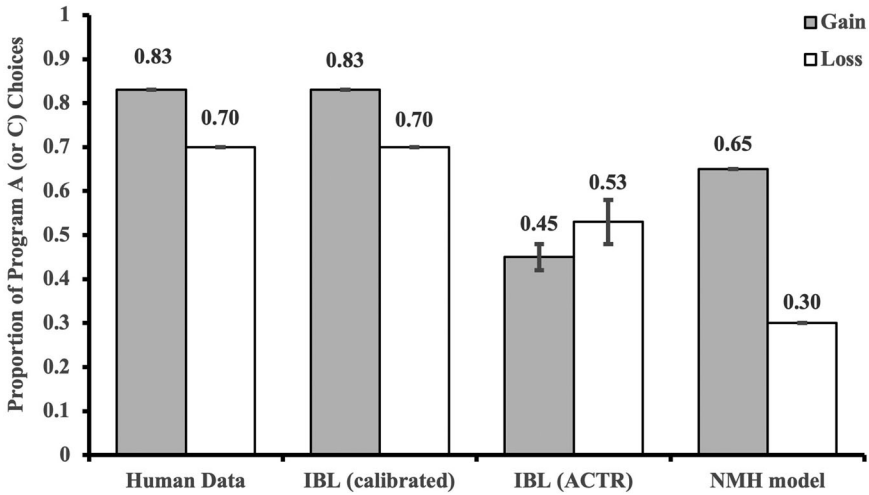
Fig. 7. The proportion of program A (gain condition) choice or program C (loss condition) choice in human data, IBL models, and NMH model in Asian disease problem (ADP). The error bars show a 95% CI around the average estimate.
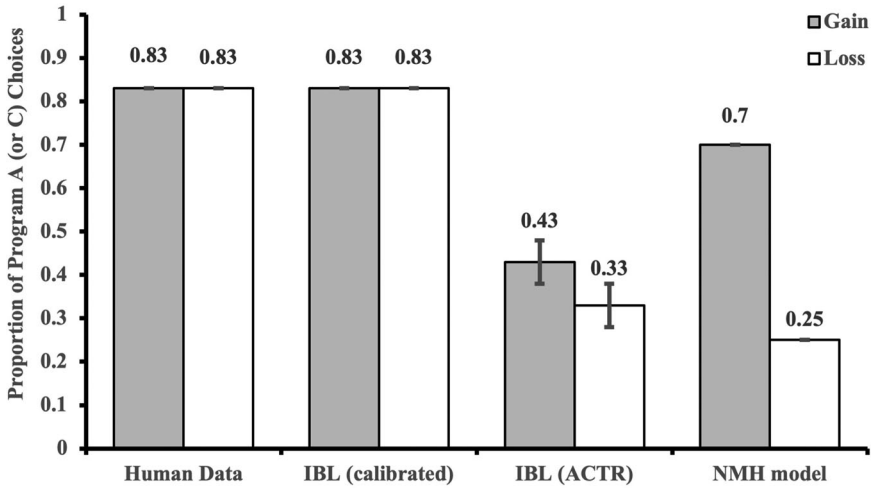
Fig. 8. The proportion of program A (gain condition) choice or program C (loss condition) choice in human data, IBL models, and NMH model in Coronavirus disease problem (CDP). The error bars show a 95% CI around the average estimate.

6.1. Performance evaluation

AIC (Akaike, 1974) was used to rank the models based upon their performance in accounting for human choices. Table 3 shows the AIC values of all the models along with their ranks. The calculation of AIC has been explained in several past publications

Table 3
Ranks of different models developed to account for human choice across gain and loss conditions in ADP and CDP problem types

		AIC (number of parameters, number of trials)			
		ADP		CDP	
AIC rank	Model	Gain condition	Loss condition	Gain condition	Loss condition
1	IBL (calibrated)	−0.61 (2, 1)	−0.61 (2, 1)	−0.61 (2, 1)	−0.61 (2, 1)
2	NMH	3.00 (0, 1)	3.14 (0, 1)	3.09 (0, 1)	2.83 (0, 1)
3	IBL (ACTR)	6.94 (2, 1)	7.04 (2, 1)	6.89 (2, 1)	7.04 (2, 1)

(Dutt & Gonzalez, 2012b, 2013; Sharma & Dutt, 2017). The AIC values for all three models given in Table 3 were calculated using Eq. 2. Each model participant was given one trial to make the final consequential choice after sampling the available choices in the sampling phase. Therefore, the number of trials (t) for all three models was 1. Additionally, the number of parameters (k) for both IBL models (calibrated and ACT-R) was 2, and for the NMH model, it was 0. The IBL (calibrated) with the least AIC value was the best performing model (–0.61).

7. Discussion

Prior research in the decision under risk experimented with problem framing in the ADP (Gonzalez & Mehlhorn, 2016; Kühberger, 1998; Ludvig et al., 2012; Tversky & Kahneman, 1981; Tversky & Kahneman, 1992). Participants were presented with a problem in gain and loss frames across description and experience formats (Gonzalez & Mehlhorn, 2016; Tversky & Kahneman, 1981). These experiments showed preference reversals in description-based ADP and the absence of preference reversals in experience-based ADP (Gonzalez & Mehlhorn, 2016; Tversky & Kahneman, 1981). However, little was known about the existence of preference reversals in problems with a specific context (e.g., COVID-19) and in description and experience formats across different problem frames. Also, little was known about how cognitive models would account for human choices under risk across different problem frames and problem types in the experience format. The main objective of this paper was to address these literature gaps and develop cognitive models to account for human choices.

Our results revealed that more people preferred safe choices in ADP; whereas, fewer people preferred safe choices in CDP. Thus, there seems to be an effect of the COVID-19 context on people's decision making. A likely reason for this result could be that risk-seeking behavior is more likely to be observed in a familiar loss-making CDP situation compared with a less familiar loss-making ADP situation (Tversky & Kahneman, 1981). Perhaps, the COVID-19 context and the prevailing pandemic and its losses made people risk seeking. In addition, this result is consistent with the prior research that reported context to influence decisions

(Brunstein et al., 2010; Dutt & Gonzalez, 2012b; Gigerenzer & Hug, 1992; Sharma et al., 2018; Tversky & Simonson, 1993; Wulff et al., 2015). However, this result contrasts with the findings of Bless et al. (1998), who showed the absence of preference reversal when context cues were present. One possible explanation for this contradiction is that the context cue presented by Bless et al. (1998) as "statistical research" could have triggered participants to analyze the available options very thoroughly and logically before making a final decision, thereby eliminating the preference reversal.

Results also revealed a combined influence of problem framing and type on consequential decisions. In the loss frame, more people seem to choose the risky option in the CDP compared to the ADP. However, no such difference could be found in people's choices in ADP and CDP in the gain frame. This result agrees with our finding that risk-seeking behavior is more likely encouraged in a familiar and prevailing COVID-19 pandemic situation rather than in an abstract and less specific Asian disease situation. Perhaps, these results also point to the presence of availability bias in people's decision (Tversky & Kahneman, 1973), where people judge the likelihood of something that is familiar and one that comes easily to mind (e.g., COVID-19) to be more likely compared to something that is less familiar and one that comes to mind with difficulty (e.g., Asian disease).

Moreover, there was an influence of problem type and format on human decisions. Though there was no difference in the consequential choices between description and experience in ADP, more people preferred choosing the risky options in description compared to the experience in CDP. Thus, the effect of underweighting and overweighting of probabilities seems to be present only in problems where context is available (Hertwig & Erev, 2009; Sharma et al., 2018).

According to our model results and AIC performance evaluation, the IBL (calibrated) performed remarkably well compared to the IBL (ACTR). These results are an extension of the work of Gonzalez and Mehlhorn (2016), where Gonzalez and Mehlhorn (2016) developed an IBL (ACTR). Based on the calibrated parameter, it can be observed that human decisions are certain when driven by reliance on recent and frequent observations in the experience format. Besides, the assumption of low recency and reasonable variability made by the ACT-R parameters in the IBL model of Gonzalez and Mehlhorn (2016) may not exist in the experience format.

The results of the IBL (calibrated) also show that there is a higher reliance on recent observations in specific context problems (CDP) compared to general context problems (ADP) in the loss frame. These results are consistent with the experimental findings of Hertwig et al. (2004) that decision making in rare events is dependent on the recently sampled information.

The NMH model developed to incorporate the combined effects of sample size, frequency of the observed outcomes, and utility associated with each outcome could not account for the human choices. Therefore, we can say that although the NMH model considered the frequency of the observed outcomes as one of the criteria to predict human choices, it was not able to account for human choices as accurately compared to the IBL (calibrated).

Our research contributes to the cognitive science community by empirically determining the influence of frame, experience, and context on people's preferences under risk. We highlight our contribution by presenting different cognitive models and how these models account

for human choices under risk. Our experimental findings suggest that people show risk-seeking behavior when presented with a specific problem type compared to general problem type. Furthermore, our research shows that, in the negative (or loss) frame and the experience format, more risk-seeking behavior is observed in specific conditions compared to general conditions. Our model results suggest a higher reliance on recently and frequent observed outcomes when making decisions in specific situations than general conditions.

Recent advancements in artificial intelligence have seen massive success due to the development of large-scale deep learning architectures used in image classification, speech recognition, reinforcement learning, and many more. These architectures (such as convolution neural networks in image classification and experience replay in deep reinforcement learning) have been inspired by natural forms of cognition. Cognitive algorithms, such as the IBL, have several advantages over existing machine learning algorithms. First, the IBL performs similarly to humans in making dynamic decisions compared to machine learning algorithms (Gupta, Roy, & Dutt, 2021). The inclusion of IBL-like cognitive techniques in machine learning algorithms may help machine agents to learn in human-like manner while training and transferring their knowledge to newer environments. Second, the IBL's memory module ensures transparency in the model's decision-making process. The contents of the memory, that is, the stored instances, can be retrieved at any point in time to interpret the model's decision. This interpretability is missing from artificial intelligence algorithms like deep neural networks and state-of-the-art deep reinforcement learning algorithms, such as Soft-Actor Critic (Haarnoja, Zhou, Abbeel, & Levine, 2018) and Twin Delayed Deep Deterministic Policy Gradient (Fujimoto, Hoof, & Meger, 2018). Third, inspired by the concept of variability in human behavior and decisions from Siegler and Shipley (1995), the IBL provides a natural and comprehensive way to explain the variance in human choice across participants. The cognitive noise parameter measures participant-to-participant variability in instance activations.

Cognitive algorithms, such as the IBL, can be used to develop contextual AI models that can work as decision aids to people (Kumar & Dutt, 2018; Lysaght, Lim, Xafis, & Ngiam, 2019; Phillips-Wren, 2012), where these models alert people when people are about to make a preference, which might be inconsistent with the expectation. Such decision aids may help people become better decision-makers, and this approach may cut across several domains and specializations.

A limitation of this research is that the CDP was presented as a context-specific problem type during the COVID-19 pandemic. The framing of such a context-specific problem during the pandemic might have caused the participant to suffer from certain cognitive biases (such as confirmation bias (Nickerson, 1998) or availability bias (Tversky & Kahneman, 1973)) while making the final decision during the experiment. Future research may repeat this study once the pandemic is over to investigate whether the pandemic influenced people's decisions.

From a modeling perspective, a limitation of using the IBLT and NMH for developing computational cognitive models is that neither of these models contain mechanisms that are sensitive to problem framing (gain/loss) or problem type (general/specific). Therefore, to accurately model the data, it became necessary to recalibrate model parameters for each condition to approximate the effect of problem framing and type. Developing computational cognitive models of human decision making that are affected by how the problem is

described remains a matter of future work, crucial for building better formal theories of human decision.

8. Conclusion

Our research has some implications for the cognitive science and artificial intelligence community. We find evidence that the presence of context encourages risk-seeking behavior among individuals when a problem is presented in a familiar negative (or loss) frame. Additionally, the effect of underweighting and overweighting of probabilities is present in context-based situations, but it is absent in abstract situations. Furthermore, the reliance on recency and frequency of outcomes during information sampling drives the final choices made by humans in the experience format. This reliance on recency and frequency of outcomes may also be one of the factors encouraging risk-seeking behavior among individuals in a context-specific negative frame.

Further investigation may be carried out on the combined influence of problem framing, problem format, and problem type on economic decision making (Druckman, 2001). Additionally, cognitive models like the IBL based upon ACT-R theory (Anderson, 2007; Anderson & Lebiere, 1998; Bothell, 2008; Ritter et al., 2019) may be compared with cognitive models developed using other architectures like SOAR (Laird, Newell, & Rosenbloom, 1987) and Clarion (Sun, 2005). To suit various framing problems, one could also try different ensemble models combining the IBL model's ideas with those from other models. This paper assumed only the base-level activation and the ACT-R theory's cognitive noise in explaining the framing effect in IBL models. Nevertheless, other ACT-R parameters, such as spreading activation and partial matching, may also be investigated for experimentation and modeling as part of future work. We plan to continue experimenting with some of these ideas in our ongoing research in experiential decisions.

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