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Illusory causation and outcome density effects with a continuous and variable outcome

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Abstract

Illusory causation is a consistent error in human learning in which people perceive two unrelated events as being causally related. Causal illusions are greatly increased when the target outcome occurs frequently rather than rarely, a characteristic known as the outcome density bias. Unlike most experimental designs using binary outcomes, real-world problems to which illusory causation is most applicable (e.g. beliefs about ineffective health therapies) involve continuous and variable consequences that are not readily classifiable as the presence or absence of a salient event. This study used a causal learning task framed as a medical trial to investigate whether outcome density effects emerged when using a continuous and variable outcome that appeared on every trial. Experiment 1 compared the effects of using fixed outcome values (i.e. consistent low and high magnitudes) versus variable outcome values (i.e. low and high magnitudes varying around two means in a bimodal distribution). Experiment 2 compared positively skewed (low density) and negatively skewed (high density) continuous distributions. These conditions yielded comparable outcome density effects, providing empirical support for the relevance of the outcome density bias to real-world situations in which outcomes are not binary but occur to differing degrees.

Keywords: illusory causation; outcome density; causal learning; contingency learning

Introduction

Many of the decisions we make in everyday life are motivated by beliefs about cause and effect. Based on the perceived contingencies between events, humans act on the environment in order to maximize desirable outcomes (e.g. taking vitamin supplements to improve health) or prevent undesirable ones (e.g. using insect repellent to prevent mosquito bites). A strategy people often rely on to make inferences about causal relationships is that the occurrence of the potential cause should alter the probability of the outcome (Jenkins & Ward, 1965). Simple contingency learning experiments test this premise. Typically, they involve two binary events—one potential cause or cue (C) and one outcome (O)—yielding four possible combinations of cause and outcome, shown in Table 1.

Manipulations of the covariation between cue and outcome are possible by varying the relative frequency of each trial type, with the resulting contingency conveniently quantified using the Δp metric (Allan, 1980), according to Equation 1.

Table 1: Contingency matrix showing the four different trial types as a function of whether the cue and outcome are present or absent.

	Outcome Present	Outcome Absent
Cue Present	*a*	*b*
Cue Absent	*c*	*d*

Equation 1:

$$\Delta p = p(O|C) - p(O|\sim C) = [a/(a+b)] - [c/(c+d)]$$

According to this rule, the contingency between two events is dependent on the probability of the outcome occurring when the cue is present and when the cue is absent. If a cue generates the outcome, Δp is positive, whereas if a cue prevents the outcome from occurring, Δp has a negative value (i.e. the outcome is more likely to occur when the cue is absent). Importantly, when a cue has no real effect on the outcome, p(O|C) = p(O|~C), Δp is zero.

Although people are often accurate when assessing causal relationships (Wasserman, 1990), research has shown that under certain conditions, we are misled to believe a causal link between a potential (but ineffective) cause and an outcome (Alloy & Abramson, 1979). Specifically, judgments of causation consistently deviate from the Δp rule when there is no contingency between the cue and the outcome (i.e. Δp = 0) and, as described below, when the frequency of *a* trial types is relatively high.

The illusion of causality is an important phenomenon because it represents a consistent error in human learning that is thought to contribute to the development and maintenance of superstitious beliefs and pseudoscientific thinking (Matute, Yarritu & Vadillo, 2011). Pseudoscientific beliefs are grounded in causal illusions, whereby two unrelated events such as consuming echinacea (i.e. an action or cue) and common cold prevention (i.e. outcome) are believed to be related in some meaningful way (Karsch-Völk, Barrett & Linde, 2015; Allan & Arroll, 2014). Despite the lack of supporting evidence for the efficacy of certain complementary and alternative medical treatments, many people still believe in their effectiveness and may even prefer such treatments over those that are scientifically validated (Lilienfeld, Ritschel, Lynn, Cautin, & Latzman, 2014).

Illusory causation and event densities

Manipulations that increase cue-outcome coincidences (i.e. trial type *a* in Table 1) appear to be particularly effective in inflating causal judgment, regardless of whether the two events are actually causally associated with one another (Wasserman, 1990; Blanco, Matute & Vadillo, 2013). Many of the studies on illusory causation have thus explored the frequency of the cue and outcome on generating a false association.

Outcome density (OD) bias refers to the tendency to overestimate the relationship between cue and outcome when the outcome occurs frequently. In a classic example, Alloy and Abramson (1979) asked participants to determine the degree of control they possessed over the onset of a green light by pressing a button. In conditions where the button press had absolutely no effect on the light, participants were more likely to overestimate the action-outcome relationship when the light frequently turned on than when it rarely turned on. This outcome density effect has now been replicated across a wide variety of learning tasks with zero-contingency events (e.g. Blanco & Matute, 2015). A high outcome density increases the frequency of *a* and *c* trials relative to *b* and *d* trials (Table 1), even though contingency remains zero. Similarly, when the probability of the cue is high (inflating the frequency of *a* and *b* trials relative to *c* and *d* trials), participants typically report greater causal judgments than when the cue rarely occurs (Allan & Jenkins, 1983).

Causal learning about real-world outcomes

Illusory causation is highly applicable to the formation and maintenance of beliefs about alternative therapies for minor illness. For example, complementary and alternative medicine is regarded as the preferred treatment for back pain in the United States (White House Commission on Complementary and Alternative Medicine Policy, 2002); an illness with a high rate of spontaneous remission analogous to the light bulb spontaneously turning on frequently in outcome density experiments (e.g. Alloy & Abramson, 1979; Blanco & Matute, 2015).

Not surprisingly, the assessment of treatment-outcome relationships in the real world often proves to be more difficult than when emulated in the laboratory. Complex, continuous, and variable consequences experienced and observed in the real world differ substantially from the deliberately simple, unambiguous and binary outcomes used in most contingency learning experiments (e.g. a light bulb turning on or not). Real-world outcomes often involve continuous and variable changes that do not fit neatly into the outcome-present versus outcome-absent dichotomy.

This issue was highlighted by Marsh and Ahn (2009) in the context of parsing ambiguous cues. They noted that the task of parsing events into discrete categories is often not a trivial problem, yet is ignored by simple covariation-based models. Covariation-based models, including associative learning models (e.g. Rescorla & Wagner, 1972), as well as causal induction models (e.g. Cheng, 1997) anticipate illusory learning effects, and the outcome density bias in particular, by assuming a certain mental representation of cue-outcome coincidences. These models are usually implemented by classifying, in a dichotomous fashion, whether the cue and outcome are each present or absent, in line with the four discrete trial types shown in Table 1. In other words, each experience can be classified as supporting or disconfirming the putative causal relationship.

Most real-life situations are sufficiently complex, which presents a problem to the way in which these models are applied. To illustrate, most medical treatments produce some outcome in varying degrees (e.g. patient is still sick or patient gets better), and rarely if ever produce no outcome at all. However, it is unclear whether people readily parse their experiences of continuous variable events into the presence versus absence of a target outcome. As such, it is important to test whether continuous outcomes produce lawful variations in illusory causal judgments in the same way as a simple binary outcome. Thus, we were interested in measuring illusory causation and outcome density effects using continuous and variable outcomes that are always present to some extent and may be difficult to dichotomize.

The current study

The aim of the current study was to test whether illusory causation and outcome density effects could be generated using an outcome that always occurred but to a varying degree. Our study used a contingency learning task framed as a medical trial for a new fictitious drug. Participants were presented with a causal scenario and instructed to make judgments about the relationship between a drug cue and health improvements. Rather than using discrete outcome events, an outcome was presented on every trial, but its magnitude varied along a continuous scale. Participants then observed a series of trials with and without the drug, with the drug actually having no impact whatsoever on recovery ($\Delta p = 0$ and precisely the same distribution of outcome magnitudes for trials with and without the drug). In both Experiments 1 and 2, participants were separated into Low and High Outcome Density (OD) conditions, where the outcome was improvement in patient's health. Low OD participants observed outcomes that were predominantly low in magnitude (i.e. little improvement in health) with some high-magnitude outcomes (i.e. large improvement in health), whereas High OD participants observed predominantly high-magnitude with some low-magnitude outcomes.

In Experiment 1, we used distributions of outcomes centered on a high (80) and low (20) mean value, and tested whether the presence of variability in the outcome around these mean outcomes affected illusory causation and outcome density effects (Variable vs. Fixed outcomes). In Experiment 2, all participants were presented with continuous and variable outcomes sourced from a single skewed distribution, with either a high or low modal value (see Figure 1). As in most OD studies, the critical measure was participants' causal judgments about the cue, in this

case measured using ratings of how effective the drug was in treating the disease relative to no treatment.

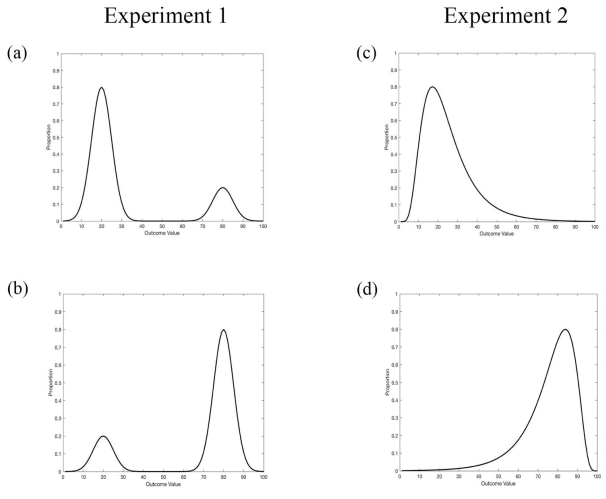

Figure 1: (a) Bimodal outcome distribution presented to participants in Variable outcome and Low OD condition, where 80% of outcomes were low in magnitude. (b) Bimodal outcome distribution presented to participants in the Variable outcome and High OD condition, where 80% of outcomes were high in magnitude. (c) Continuous outcome distribution presented to participants in the Low OD condition, where 80% of outcomes were below an outcome value of 50. (d) Continuous outcome distribution presented to participants in the High OD condition, where 80% of outcomes were above an outcome value of 50.

Experiment 1

Method

Participants. One hundred and twelve participants (78 female, M_{age} = 22.2, *SD* = 5.35) completed the study for class participation or monetary reimbursement. Participants were randomly allocated to one of four experimental conditions according to time of arrival (n = 28 in each).

Design. The study used a 2 (OD: High vs. Low) x 2 (Outcome Variability: Fixed vs. Variable) between-subjects design. For participants in the Variable outcome condition, the observed outcome was sampled from a low distribution (*M* = 20, *SD* = 5, *Range* = 13-27) or high distribution (*M* = 80, *SD* = 5, *Range* = 73-87) depending on OD group. In contrast, participants in the Fixed outcome variability condition were presented with an exact-value outcome of 80 on 80% of trials and 20 on 20% of trials in the High OD condition, and an exact-value outcome of 20 on 80% of trials and 80 on 20% of trials in Low OD condition.

The experiment was programmed using Matlab and the Psychophysics Toolbox extensions (Brainard, 1997; Pelli, 1997). All participants completed 100 training trials, 50 with and 50 without the treatment cue. Trials were presented to participants in blocks of 10 such that each block was representative of the total frequency of high and low outcomes in the experiment (Table 2).

Table 2: Proportion of total trials (per block and overall) in low and high outcome density conditions. Blocks of 10 trials were presented 10 times, yielding 100 trials.

	Low OD group		High OD group	
	Cloveritol	No treatment	Cloveritol	No treatment
High Outcome	0.1	0.1	0.4	0.4
Low Outcome	0.4	0.4	0.1	0.1

Procedure. Participants were asked to imagine they were a medical researcher investigating a new illness. They were told a new experimental drug 'Cloveritol' had been created to treat the disease. The objective of the study was to test the drug's efficacy in treating the disease. All participants were told that patients usually take a long time to recover, and a large improvement in health is indicative of rapid recovery.

During training, participants were presented with trials in which they were asked to predict the level of improvement in the patient's health. Each trial represented a new patient and participants were shown if the drug was administered (represented by a picture of a pill bottle and drug name), or not administered ('No treatment'). Below this cue, a scale was presented ranging from 0% (no improvement) to 100% (full recovery), and participants were required to predict the patient's health in that trial by clicking on a point on the scale. Once a prediction was made, an identical scale would appear below with the actual observed health improvement for that trial animated as a growing horizontal bar across the scale. Task schematics are illustrated in Figure 2.

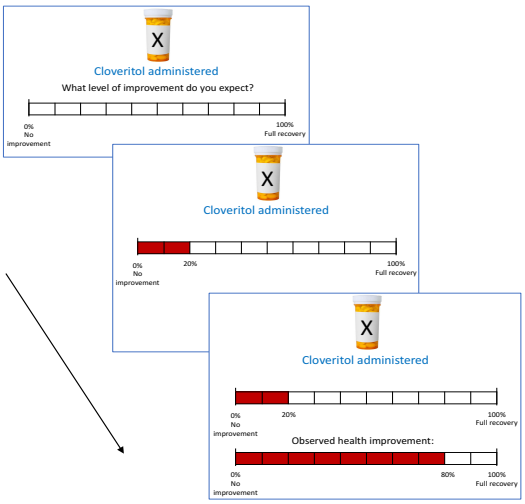

Figure 2: Typical displays during the training phase in Experiment 1 and 2. Participants are presented with either the drug cue (Cloveritol administered) or no cue (No Treatment) and asked to make a prediction on the patient's health improvement. Having done so, a second scale appears with the observed outcome for that patient.

During test, participants were instructed to make judgments about the treatment based on observations during training. Participants were first presented with the drug cue and no treatment cue separately with instructions to predict the level of improvement they would expect *on average* if a patient were given Cloveritol or No Treatment. Ratings were made on the same scale as presented during training. Subsequently, they were asked to rate how effective they thought the treatment was relative to no treatment. Ratings were made on a scale from 0 (Completely Ineffective) to 10 (Completely Effective).

Results

We focus first on the results of critical importance, namely the effect of outcome density, and its interaction with outcome variability, on judgments of treatment efficacy. Causal judgments of this nature have most consistently produced OD effects in previous studies and we expected these ratings to show the effect most reliably in our study. These efficacy ratings are illustrated in Figure 3. As predicted, we found a main effect of OD, $F(1,108) = 11.3$, $p = .001$, $\eta_p^2 = .094$, such that participants in the High OD condition ($M = 4.73$, $SD = 2.69$) reported significantly greater efficacy ratings than participants in the Low OD condition ($M = 3.11$, $SD = 2.34$).

Critically, we found no significant interaction effect between OD and outcome variability, $F(1,108) = .004$, $p = .953$, $\eta_p^2 < .001$, suggesting that the OD effect did not differ significantly between groups. Indeed, significant OD effects were found when participants were presented with Variable outcomes, $F(1,108) = 5.43$, $p = .022$, $\eta_p^2 = .048$, as well as when they were presented with Fixed outcomes, $F(1,108) = 5.83$, $p = .017$, $\eta_p^2 = .051$.

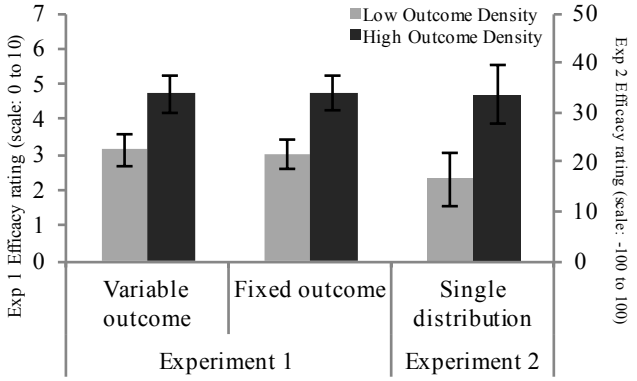

Figure 3: Drug efficacy ratings at test (±SE) as a function of OD and outcome variability in Experiment 1 (left) and for Low vs High OD conditions in Experiment 2 (right). Efficacy ratings were measured on a scale ranging from 0 (Completely Ineffective) to 10 (Completely Effective) in Experiment 1, and from -100 (Effectively worsens recovery) to 100 (Effectively improves recovery) in Experiment 2. Negative efficacy judgments in Experiment 2 indicates that the drug makes patients feel worse, whereas positive values suggest the drug improves patient recovery.

Table 3: Average rating for Cloveritol and No Treatment at test (SD) as a function of Outcome Density (Low vs High) and Outcome Variability (Fixed vs Variable).

	Low OD		High OD	
	Cloveritol	No treatment	Cloveritol	No treatment
Exp 1 Fixed	34.1 (13.7)	32.6 (14.0)	68.0 (13.8)	59.3 (17.4)
Exp 1 Variable	34.8 (14.7)	32.8 (16.1)	71.5 (15.2)	67.5 (15.4)
Exp 2	44.1 (12.4)	36.3 (15.0)	69.6 (12.4)	53.3 (16.7)

Average outcome magnitude predictions for Cloveritol and No Treatment at test are reported in Table 3. We found a significant main effect of cue type on average predictions, $F(1,108) = 6.37$, $p = .013$, $\eta_p^2 = .056$, with greater average ratings for Cloveritol ($M = 52.1$, $SD = 22.7$) than No Treatment ($M = 48.1$, $SD = 22.1$). This finding suggests an illusory causation effect. Participants were predicting greater health recovery when the drug was present than when it was absent, despite there being no contingency between cue and outcome. However, this effect of cue type did not interact with outcome density, $F(1,108) = 2.00$, $p = .160$, $\eta_p^2 = .018$; this was true for both outcome variability conditions, $F < 1$. This null interaction is not uncommon in work on illusory causation, which tends to produce outcome density effects on causal ratings rather than on direct predictions of the outcome.

Discussion

Experiment 1 found a clear OD effect in efficacy judgements at test using a variable outcome distribution. The High OD condition produced greater efficacy ratings than the Low OD condition and this difference was consistent across Fixed and Variable outcome conditions. We consider this result to be highly consistent with other studies that have used discrete binary outcomes. Similar outcome density effects were not found when participants were asked to provide an average prediction for treatment cue and no treatment cue at test. This discrepancy in causal judgments as a function of question format has been extensively discussed elsewhere (see Vadillo & Matute, 2007). Importantly for our purposes, previous research has consistently found this discrepancy, which supports our claim that the adopted experimental design did not significantly differ from traditional binary-outcome contingency learning paradigms.

In this experiment, the outcome magnitudes were sampled from two distinct and non-overlapping distributions, each with relatively low variance. Thus categorizing them as two discrete outcomes (high and low) may still be relatively straightforward for the participant. It is still important to demonstrate that OD biases generalize to situations in which the distribution is not so distinctly partitioned. Experiment 2 examined the same outcome

density effects by using a continuous outcome distribution, in which all participants experience a full range of outcome values.

Experiment 2

Experiment 2 was identical to Experiment 1 in all respects except the way in which outcomes were distributed. Instead of a bimodal distribution with values centered around 20 and 80, participants experienced outcome values sourced from a single distribution, and ranging from 1 to 99. Similar to Experiment 1, participants in the Low OD condition experienced a majority of low-magnitude outcomes with some high-magnitude outcomes, and this was reversed for participants in the High OD condition. All outcomes presented were independent of the cue.

A central difference between the distribution used in Experiment 2 and that of Experiment 1 is the addition of ambiguous outcome values around the mid-range of the scale that are less readily classifiable as low-magnitude or high-magnitude outcomes. We were interested in determining whether we could still obtain outcome density biases in a trial-by-trial contingency learning task with the use of continuous and variable outcomes sampled from a complete range of values, some of which are more decipherable to the participants (low vs. high) than others.

Ratings of treatment efficacy presented at test were modified to capture greater variance in responses, with values ranging from -100 (Effectively worsens recovery) to 100 (Effectively improves recovery) with a midpoint of 0 (Completely ineffective). This modification in Experiment 2 allowed meaningful comparisons to be made between the group means and zero, the midpoint of the scale, whereas zero represented an extreme end of the scale in Experiment 1. It is also possible that some participants judge that the drug actually makes health improvement *less* likely since the base rate of recovery without the drug was quite high.

Method

Participants. 56 participants (35 female, M_{age} = 22.9, *SD* = 4.44) completed the study for either class participation or monetary reimbursement and were randomly allocated to one of two experimental conditions (n = 28 in each).

Design. The study used a between-subjects design, with outcome density (Low vs. High OD) as the only manipulation. For the Low OD condition, the sample of observed outcomes *O* was positively skewed, created using a truncated ex-gaussian distribution with a higher proportion of low-magnitude outcomes (Distribution parameters: μ= 10, σ = 5, τ = 25, *Range* = 1-99, yielding sample *Mean* = 32, *SD* = 20). For the High OD condition, we took the complement of this same distribution (i.e. 100 – *O*) to produce a negatively skewed distribution with a higher proportion of high-magnitude outcomes (sample *Mean* = 68, *SD = 20*). Outcome values were further constrained by the proportion of trials with an outcome-value below 50: participants in the Low OD condition experienced .75 of trials with outcomes below 50, whereas participants in the High OD condition only experienced .25 of trials with outcomes below a value of 50. All participants received identical causal instructions and the procedure of the study was identical to that of Experiment 1.

Results

Efficacy ratings at test are shown in Figure 3. As predicted, we found a main effect of OD, $F(1,54) = 4.54$, $p = .038$, $\eta_p^2 = .078$, such that participants in the High OD condition (M = 33.6, *SD* = 31.7) reported significantly greater efficacy ratings than participants in the Low OD condition (M = 16.5, *SD* = 28.3). A comparison of the group means against zero found a significant difference for both Low OD, $t(27) = 3.09$, $p = .005$, $d' = .584$, and High OD, $t(27) = 5.62$, $p < .001$, $d' = 1.06$. These findings indicate illusory causation effect in both Low and High OD condition, with greater difference found in the High OD group. As in Experiment 1, we did not find an interaction between cue type and outcome density in average outcome magnitude ratings, $F(1,54) = 3.06$, $p = .086$, $\eta_p^2 = .054$.

Discussion

In Experiment 2, we found support for the use of continuous and variable outcomes in generating an outcome density effect, with significantly greater judgments of treatment efficacy in the High OD relative to the Low OD condition.

Together, the results from Experiments 1 and 2 indicate that reliable OD effects emerge even when the outcomes are presented in a continuous and variable manner, mirroring some important properties of real-world outcomes. Importantly, the OD effect obtained using a continuous and variable outcome was not significantly different to that from a fixed-value outcome (analogous to binary events), suggesting that the current experimental paradigm is a reliable measure of the effect in generating illusory causation.

To our knowledge, this is the first study showing OD effects with outcomes that are potentially ambiguous. That is, the magnitude of these outcomes provides information that is not always readily classifiable as confirming or disconfirming the learner's current causal hypothesis. There are two opposing explanations for this finding. Firstly, individuals may parse ambiguous outcome information into discrete categories and use this information to form judgments about causal relationships. This ability is potentially important for accurate contingency learning, but may also be instrumental in producing the errors of judgment leading to OD effects. Increasing the frequency of outcome-present trials, in this case high-magnitude outcomes, creates an over-representation of cue-outcome coincidences, resulting in stronger causal judgments. This interpretation of our findings parallels previous studies with ambiguous *cue* information, which has shown learners to spontaneously categorize ambiguous intermediate observations in a discrete fashion and use them in subsequent contingency judgments (Marsh & Ahn, 2009).

A second interpretation of these findings is that the OD effect emerges even when the learner is not able to categorize events into discrete classes. If so, these results lend themselves to Bayesian models of causal judgment (Griffiths & Tenenbaum, 2005) in which continuous representation of the expected outcome magnitude can be implemented relatively easily. Associative learning models like the Rescorla-Wagner model can also accommodate continuous outcomes by assuming that the "teaching signal" that represents the experienced outcome can take on values proportional to the outcome magnitude. These theoretical approaches may be able to account for OD effects and illusory causation without assuming discrete categorization of events by the learner. Testing the capabilities of these models is thus an important future endeavor.

The results from our experiments provide empirical support for the use of continuous and variable outcomes that mimic real-world events in obtaining an outcome density bias. This is particularly relevant for researchers interested in investigating false causal beliefs in medicine and public health, where the consequences of choosing the wrong treatment could have detrimental effects.

Conclusion

Across both experiments, we found a reliable outcome density effect, where participants who frequently observed high levels of health improvement judged a fictitious drug to be more efficacious than participants who observed levels of health improvement that were frequently low, even when there was no real contingency between drug and health outcome. This finding is compelling given the novel experimental paradigm using continuous and variable outcomes that occur on every trial but vary in degree. This approach also produced effects that were not significantly different from fixed-value outcomes analogous to binary events adopted in previous contingency learning experiments. The experimental approach we present here, that is, representing treatment outcomes in a continuous and variable fashion that mimic real-world medical consequences, may be an important stepping-stone to bridging the gap between experimental research and real-world experience.

Acknowledgments

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