Title

Perceptions and Probabilities: Influence of Increased Options on Performance Generalization Across Two Variations of the Monty Hall Dilemma

Permalink

Journal

ISSN

Authors

Southern, Robert A.
Bodily, Jessica Stagner
Bodily, Kent D.
et al.

Publication Date

DOI

Supplemental Material

Copyright Information

Peer reviewed

Perceptions and Probabilities: Influence of Increased Options on Performance Generalization Across Two Variations of the Monty Hall Dilemma

Robert Southern [1], Jessica Stagner Bodily [2], Kent D. Bodily [3] and Lawrence Locker, Jr. [4]

[1] Kansas State University

[2] Auburn University at Montgomery

[3] The Learning Tree LLC

[4] Georgia Southern University

The Monty Hall dilemma (MHD) is a probability puzzle in which humans consistently fail to adopt the optimal winning strategy. The participant chooses between three identical doors, behind one of which is a valuable prize. After the participant makes their initial decision, the host reveals that there is nothing behind one of the two remaining doors, then asks the participant if they would like to stay with their originally selected door or switch to the remaining unopened door. The optimal choice is to switch to the previously unchosen door, which increases the probability of winning from 33% to 67%. Despite this basic solution, humans repeatedly perform suboptimally. Previous attempts to improve performance by increasing the number of available doors have been successful (Burns & Weith, 2004; Franko-Watkins et al., 2003; Saenen et al., 2015; Stibel et al., 2009; Watzek et al., 2018). However, prior studies that examined whether this improved performance could generalize to different contexts have been inconclusive (Franko-Watkins et al., 2003; Watzek et al., 2018). To examine whether human performance can generalize across two computerized variations of the MHD, the present study explored how previous experience involving trials presented with eight options affects switching percentages in subsequent trials with three options. The results replicated findings from previous studies, which demonstrated that switching rates increased as a function of more available options. The findings also revealed participants can successfully generalize their behavior when returning to three-option trials. Further exploration of the MHD is needed to determine why performance generalization occurs in certain contexts but not others.

Keywords: generalization, Monty Hall dilemma, perception, suboptimal choice

The Monty Hall dilemma (MHD) is a basic probability puzzle with one optimal strategy that is notoriously challenging for humans. The dilemma originated on the game show, "Let's Make a Deal," hosted by Monty Hall from 1963 through 1986. During the game show, the contestant was presented with three identical options, classically represented by numbered doors. Behind one of these doors was an expensive prize, while the remaining doors were empty. The host asked the contestant to select one of the doors that may contain the prize. After the initial choice was made, the host revealed another door that was not selected by the contestant and did not contain the prize. Then the host presented the dilemma to the contestant by asking whether they would like to stay with the door they initially chose or if they would like to switch to the final unopened door.

To maximize the probability of winning the prize, the contestant should always switch to the remaining door. When the contestant made their initial choice, they had a 33% chance of choosing the door that contained the prize. This outcome is referred to as a "lucky guess." If the contestant made a lucky guess, the host could open either of the remaining doors since both doors do not contain the prize. By not switching, the contestant would be successful 33% of the time across a given number of trials. Alternatively, if the contestant switched, the likelihood of correctly choosing the door with the prize increased to 67%. An easier way to understand why switching is advantageous is to consider the dilemma when there are 100 doors available instead of just three. If a random door is selected and the host reveals 98 empty doors, the contestant can be almost certain that the prize is behind the unopened door that was not initially chosen. When 100 doors are available, switching results in a prize 99% of the time since the chances that the contestant's initial choice is a lucky guess is 1%. The probability of winning after staying or switching is directly proportional to the number of doors available. Therefore, switching to the remaining door is the optimal strategy because any other strategy results in a lower probability of winning on average.

Despite the disparity between the winning probability for staying and switching, humans not only fail to recognize which strategy has the highest overall probability of resulting in a winning outcome, they repeatedly exhibit a bias towards staying with their initial selection (Granberg, 1999). Granberg and Brown (1995) found that repeated exposure through multiple trials improved performance and that participants began to plateau after approximately 20 trials, switching roughly two-thirds of the time. This plateauing effect in human participants has been observed repeatedly (Efendić & Drace, 2015; Granberg & Brown, 1995; Herbranson & Schroeder, 2010; Herbranson & Wang, 2014; Hirao et al., 2017; Mazur & Kahlbaugh, 2012).

To explore how other species would perform when presented with this dilemma, Herbranson and Schroeder (2010) compared pigeon (*Columba livia*) performance to human performance using a nonverbal, computerized adaptation of this task. Human participants received 200 trials of the MHD with feedback after each trial. Like Granberg and Brown (1995), the participants' switching rates increased steadily until plateauing around 67%. Pigeons initially started with a slightly stronger stay bias, but after 30 training sessions, they developed a strong preference for switching. Furthermore, the pigeons continued performing better than the human participants, even when the researchers reversed the contingencies so that staying became reinforced two-thirds of the time. These results indicate that pigeons had greater sensitivity to the contingencies, which led pigeons to adopt the optimal strategy more efficiently and reliably than their human participants, even when the contingencies were reversed.

Further studies examined whether this suboptimal tendency was exclusive to humans by testing non-human primates (Klein et al., 2013; Watzek et al., 2018) and rats (Stagner & Zentall, 2014). Klein et al. (2013) determined that the monkeys' (*Macaca mulatta*) performance indicated a substantial comparative similarity with human performance. The results of Watzek et al. (2018) also showed considerable similarities between response patterns of capuchin (*Cebus [Sapajus] apella*) and rhesus macaques to human response patterns in both 3-door and 8-door conditions. Stagner and Zentall (2014) concluded that rats (*Rattus norvegicus domestica*, Sprague-Dawley strain), like pigeons, appeared to be influenced more by the overall probability of reinforcement, leading to similar performance between species. Overall, these studies illustrate that almost all subjects, regardless of species, had some difficulty adopting the optimal strategy, but humans seemed to have the most difficulty.

One explanation for the suboptimal performance of humans is known as probability matching. Probability matching is characterized by choice probabilities that match the pre-programmed probabilities for obtained reinforcement. This propensity to allocate responses based on associated reinforcement probabilities is typical when using probabilistic outcomes (Fantino & Esfandiari, 2002) and frequently results in less reinforcement overall. Phyletic similarities and differences in tendencies to probability-match have been observed across a range of species including rats, pigeons, monkeys, turtles (*Chrysemys picta*), and fish (*Tilapia macrocephala*; Bitterman, 1965). An example of this phenomenon occured when participants attempted to predict which colored light (green or red) would appear on an upcoming trial. The participants received a small monetary reward each time they correctly predicted the color stimulus. In this scenario, the green light appeared on 75% of trials while the red light appeared on the remaining trials. Participants could maximize their chance of success by only selecting green as the light that would appear. However, over time many participants chose green approximately three times more often than red, resulting in response patterns that mirrored the probabilities of reinforcement for each alternative (reviewed by Vulkan, 2000).

Increased amounts of anticipated regret have also explained suboptimal performances by humans in the MHD. Participants who experienced a loss after switching reported higher feelings of regret than losses that resulted from staying (Stibel et al., 2009). This finding may also explain why Petrocelli and Harris (2011) discovered that participants often exaggerated the amounts of switch-losses they experienced when asked to estimate the frequencies of loss associated with switching and staying, respectively. This increased aversion to switching due to more anticipated regret following a switch-loss rather than a stay-loss could explain why humans consistently exhibit a stay-bias. Stibel et al. (2009) attempted to test this hypothesis by manipulating whether the initial selection was randomly determined or chosen by the participant. Their results showed that participants switched more frequently when their initial selection was randomly determined than participants who freely selected their initial choice. Zentall et al. (2015) used a similar methodology of forced initial choices to examine its effect on pigeons' performance. Unlike humans, pigeons that experienced forced initial selections performed worse overall by switching less frequently than pigeons with free selection.

Anticipated regret cannot explain the common misunderstanding of this problem in humans. Still, it can potentially explain the frequently observed stay-bias in human performance, despite reporting incorrect judgments of equivalent probabilities for winning associated with staying and switching. This phenomenon among human participants in the MHD is consistent with an equiprobability bias (Gauvrit & Morsanyi, 2014). Participants falsely report that both options are equally likely to contain the prize when they estimate the probabilities of winning for the two remaining options. Human participants that report equal probabilities should not exhibit a preference for one alternative over another. However, studies have shown that participant behavior reflects a clear preference for staying despite self-reported estimates of probabilities being equal for staying and switching (Franco-Watkins et al., 2003; Granberg & Brown, 1995; Krauss & Wang, 2003; Stibel et al., 2009).

Although research has demonstrated that human performance in the MHD can improve through repeated exposure, typical performance is still well below optimal. Several studies increased the number of options available for selection to provide additional performance improvements (Burns & Wieth, 2004; Franco-Watkins et al., 2003; Saenen et al., 2015; Stibel et al., 2009; Watzek et al., 2018; reviewed by Saenen et al., 2018). Increasing the number of available options raises the likelihood that switching will result in reinforcement when all but two options have been eliminated. For example, when three options are available, switching results in reinforcement 67% of the time. That amount is increased to 87.5% if the available options are increased to eight, and six of the options that were not initially selected are eliminated. Therefore, the contestant should be more likely to switch when more options are added. Saenen et al. (2015) implemented three conditions, each with an increasing number of cups (3/10/50), then compared performance across 10 trials. Stibel et al. (2009) examined whether performance on a single trial improved by including conditions that gradually increased the number of boxes available, ranging from 5 to 10. Burns and Wieth (2004) increased their total number of options to 128 for a single trial, while Franco-Watkins et al. (2003) implemented doors ranging from 3 to 10 for three trials. Each study found that switching rates increased as a function of more available options. However, Stibel et al. (2009) found that increased switching rates remained stable, and no significant improvement occurred as additional options were added.

Previous studies have examined whether performance in one variation of the MHD can generalize to other contexts. Franco-Watkins and colleagues (2003) found inconsistent effects of generalization, but without a control group for comparison, interpreting their results becomes challenging. Watzek et al. (2018) attempted to address some of these concerns by testing whether performance from humans, capuchins, or rhesus macaques during a computerized version of the MHD would generalize to another variation of the MHD. Human participants were randomly assigned to a 3-door, 8-door, or control condition, who received an unrelated computer task, and tested using repeated trials during a 60 min session. Once the participants completed testing, they were given a survey-based "one-shot" variation of the MHD adopted from Krauss and Wang (2003).

Nonhuman subjects were tested using a contextually similar computerized variation with three or eight options, depending on the condition. Watzek and colleagues (2018) predicted that subjects (human, capuchin, and rhesus macaques) in the eight-door condition would switch more frequently than subjects in the 3-door condition during initial testing. They also hypothesized that participants in the eight-door condition would switch more frequently than other conditions in the one-shot survey-based variation of the MHD.

Watzek and colleagues (2018) found that both human and rhesus macaques showed near-optimal responding patterns, which are highly unordinary, but only 19.8% of participants elected to switch during the one-shot variation of the task. However, generalization was observed in capuchins that experienced the eight-door condition before transitioning to the 3-door condition in the computerized version of MHD. The researchers' affirmed their prediction that more frequent switching occurred in the 8-door condition. However, their participants were primarily unable to generalize their knowledge to a description-based MHD variation, with approximately 80% choosing to stay with their initial choice.

The current study expands on the findings of Watzek et al. (2018) by examining whether the generalization effects demonstrated by capuchin monkeys will also occur with human participants. This study utilized a similar methodology that Watzek and colleagues used with the following modifications. First, square stimuli were used to represent doors in the current study instead of the unique arrangement of circular stimuli used previously. Secondly, Watzek and colleagues (2018) incorporated the natural reinforcement probabilities for staying and switching instead of holding these probabilities constant between 3-option and 8-option variations. As a result, the current study maintained consistent reinforcement probabilities across all task variations. This modification eliminated the possibility that performance differences could be attributed to shifting reinforcement probabilities rather than a perceived decrease in the likelihood that their initial choice was correct as a function of experience with an increased number of available options.

Generalization is more likely to occur when two task variations have a high degree of similarity (Sousa, 2016). To provide the highest likelihood for generalization, the researchers decided to test participants using two similar variations of the computerized MHD task instead of one computerized MHD variation and another survey-based, one-shot variation of the dilemma used by both Watzek et al. (2018) and Franco-Watkins et al. (2003). The total number of trials given to each participant in the current study was decreased to 60, compared to the 493 trials that participants completed on average in Watzek et al.'s (2018) study. In addition, the total number of trials was reduced so that acquisition could be monitored within each phase while reducing completion time.

The most extensive change to the methodology used by Watzek et al. (2018) to demonstrate generalization in capuchins involves stimulus presentation structure. Watzek and colleagues presented the same number of stimuli in each condition while varying the order in which the stimuli were presented. For example, in one condition capuchin subjects received 500 trials of a computerized MHD task with three doors in their experiment, followed by 500 trials of a similar task with eight options. Monkeys in the other condition received 500 trials of the 8-option computerized MHD task before receiving 500 trials of the 3-option variation. The current study modified this A-B/B-A design into an A-B-A or A-A-A design for the experimental and control conditions, respectively. The A-phase consisted of trials with 3-options, and the B-phase consisted of 8-option trials. This adaptation also provides within-subjects and between-subjects points of comparisons while controlling for any potential order effects that might have been present previously.

The present study expanded on the previous findings by Watzek et al. (2018) in human participants by examining whether prior experience with an 8-option computerized variation of the MHD generalized to improve performance in a computerized variation with three options. We predicted that participants in the experimental condition would switch more frequently in Phase 2. In that case, this finding would suggest that the participants changed their perception regarding the likelihood that their initial choice was a lucky guess. For example, during three-option trials, participants are more likely to perceive their initial choice as having a higher likelihood of being correct (33%) than in 8-option trials (12.5%). This change in perception was expected to occur even though the participants were unaware that the likelihood of a "lucky guess" remains constant in both variations.

We also predicted that improvements in participants' performance would generalize to Phase 3 despite reinforcement probabilities remaining constant. Together, these results would indicate that this perceptual change was able to generalize to different variations of the dilemma. These findings would provide evidence that human performance in this dilemma can be improved, and that this improvement can be translated into novel contexts. If successful, this result would be the first step in demonstrating how improved performance in the MHD can generalize to other scenarios while providing the foundation needed to determine which mechanisms affect how participants respond under uncertainty.

To test these predictions, all participants experienced 20 trials of the classic MHD with three available options to establish a baseline performance level. Then, participants in the experimental condition completed Phase 2 with eight available options for an additional 20 trials before beginning Phase 3 consisting of 20 final trials, identical to Phase 1 (i.e., the same classic form of MHD). To our knowledge, this is the first study in which the reinforcement probabilities for switching (67%) and staying (33%) remained constant despite increasing the number of available options. Therefore, any effect on performance can be attributed to manipulating the increased number of options available and not to changes in reinforcement probabilities.

Method

Participants

Participants ($N = 112$, 73.2% female, 25.8% male, 1% other) were undergraduate psychology students from Georgia Southern University who participated for course credit. All participants were at least 18 years of age and provided informed consent before beginning the study. At the end of the session, participants were asked to indicate whether they were familiar with the Monty Hall dilemma and its optimal strategy before participating. If the participants answered "Yes" to both questions, their data were excluded from the analysis. Data from participants that indicated familiarity with the MHD but not its optimal strategy were not excluded. Data from one participant was excluded from analyses based on these criteria.

Materials

The experimental task was programmed using AngularJS version 1.8.0. The program was hosted using Bluehost web hosting services. After a participant registered via SONA Systems, a hyperlink was made available containing information about the informed consent policy and instructions for participants. In addition, a link to an external survey was also included so that participants could confirm their participation while their data remained anonymous. This link appeared at the beginning and end of the experiment. Once the participant provided informed consent, the instructions were presented (see Appendix A), followed by the experimental trials.

Square stimuli measured 128 pixels, and the center square was located 13 cm from the top of the screen and 21.9 cm from the left-hand side of the screen. Subsequent squares were arranged equidistant from the center square by 0.635 cm. All measurements were made using a monitor with an aspect ratio of 1920x1080. Precise locations of stimuli varied based on the device used by each participant. When a square was selected, it was indicated by two intersecting lines in the form of an "X" for one second before reverting during the following selection process. Once a selection was made, one to six squares became "revealed" depending on the condition. These revealed squares remained black for the trial's duration and could not be selected until a new trial began (see Figure 1).

Design and Procedure

This project was reviewed by the Georgia Southern Institutional Review Board (H21237). Participants were randomly assigned to the Experimental or the Control group using a random number generator before the first trial began. Participants in the Experimental group completed three consecutive phases in a standard A-B-A experimental design. To examine acquisition curves within each phase, all phases consisted of 20 trials. For the Experimental group, the first and third phases included three options for selection, whereas the number of available options increased to eight during Phase 2. The number of options available for selection during the terminal choice remained the same regardless of phase. Participants in the Control group experienced three identical phases with three options for selection across all trials. All participants were informed of their rights and provided informed consent before the experiment began. After obtaining consent, the participants were provided instructions for completing the task.

The experiment began after the participants clicked a button labeled "Begin." For participants in the Experimental group, Phase 1 consisted of 20 trials with three options available to be chosen (see Figure 1). After the participant's initial selection, the selected square became marked, while a different square, chosen at random, became solid black. After 1 s, the marked square returned to its previous form, leaving two identical squares that could be chosen. Finally, the participant made their terminal choice (either retaining their initial selection or switching to the available option), and their selected square became marked once more. After one second, all stimuli disappeared, and feedback was delivered in the form of "You win! Try again" on winning trials or "You lose. Try again" on losing trials. Feedback remained visible for two seconds before an inter-trial interval (ITI) consisting of a blank white screen appeared for one second, after which a new trial commenced.

The outcome of the trial (win or loss) was determined by a random number generator that pulled a number between 1–100. This number was generated once the participant chose to stay or switch, not at the start of the trial. This way, these probabilities would be constant no matter how many options were available. Once a number was generated, the program examined whether the participant chose to stay or switch. If the participant chose to stay, numbers ≤ 33 were considered wins, while numbers ≥ 34 were considered wins if the participant chose to switch.

Figure 1

Experimental Group Example Trials
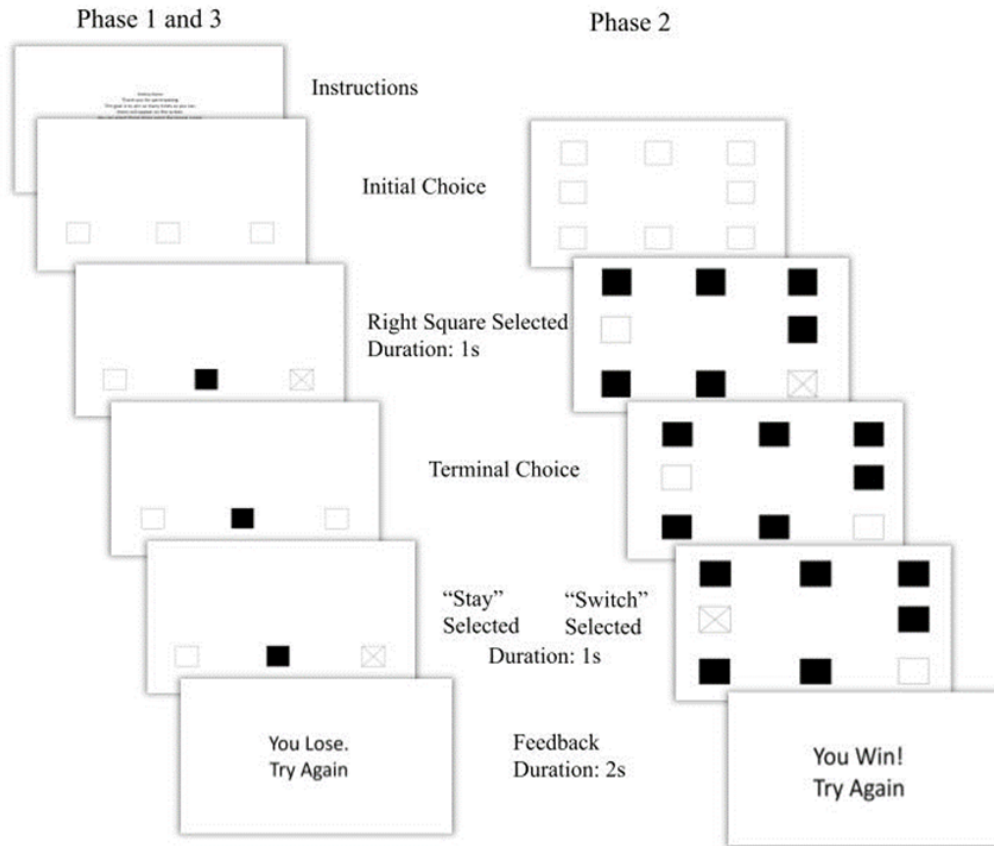
Note. Black squares denote revealed options and cannot be selected. Intersecting lines represent selected squares. Instructions are only presented before the first trial commences.

After 20 trials, Phase 2 began. Participants in the Experimental group were presented with eight options rather than three. Note that reinforcement probabilities for staying and switching remained constant across every trial regardless of condition. Like Phase 1, once an option was selected, it was marked while six of the remaining seven squares were simultaneously eliminated as choices that could not be selected. After a one second delay, the participant made their terminal choice. Again, the chosen square became marked for one second before feedback was delivered, and an ITI was presented. Once 20 more trials occurred, Phase 3 began. For the control condition, Phase 2 and Phase 3 were simply a continuation of Phase 1 (i.e., three available options). For both conditions, the first and third phases were identical in presentation.

Upon completing all three phases, participants in both conditions were presented with a series of questions. Participants were first asked to indicate their gender. Next, participants indicated whether they were familiar with the MHD, also known as the 3-Door problem, before beginning the experiment. Participants who responded "Yes" to the first question were asked if they knew the dilemma's optimal strategy before beginning the experiment. Finally, participants described their strategy during the task in an open-response format. Upon completing the survey questions, participants were given a short description debriefing them about the experiment's purpose and potential implications. The researcher's contact information was provided along with the external survey link to ensure participants were properly compensated for participating.

Data Analysis

Raw choice data were analyzed using the generalized multilevel logistic regression (GMLR) approach. All analyses were preformed using R Statistical Software (v4.2.2; R Core Team 2022).The *R* package *lme4* (Bates et al., 2015) was used for model fitting, and the *emmeans* package (Lenth, 2022) was used for post hoc comparisons using Tukey's method for adjusted *p* values. GMLR approaches reduce the likelihood of observing a Type 1 error by implementing both fixed effects (group-level) and random effects (individual level) and are the recommended data analysis technique for binomial choice data (Young, 2018). GMLR methods can also detect smaller effects by including all choice data in a model. This method is more precise when compared to traditional techniques, like analysis of variance (ANOVA), which relies on single-point means (Boisgontier & Cheval, 2016).

In the analyses, all categorical variables were effect coded. These variables included Group (Experimental and Control) and Phase (1-3). Models with Phase treated categorically rather than continuously had lower Akaike Information Criterion (AIC) values, suggesting greater model fit. Therefore, Phase was treated categorically with Phase 3 as the contrasting condition. Subtrial refers to the 20 trials within each phase. Subtrial was a continuous variable that was mean-centered to reduce multicollinearity (Iacobucci et al., 2016). Based on previous literature, switch behavior was predicted to produce a logarithmic function across subtrials, such that switching rates would begin to plateau as participants approached the end of each phase. To account for this, we included a log-transformation of subtrial as a parameter for model comparison. The outcome variable was binomial choice data, with 0 representing 'stay' and 1 representing 'switch.'

The data were modeled using a full factorial model with Group, Phase, and log(Subtrial) as fixed effects. Each model used a parsimonious random-effect structure which systematically added complexity to find the best fitting model. The random effect structure that produced the lowest AIC value was an intercept-only model (AIC = 6580.5). Models that included log(Subtrial) as a random slope resulted in higher AIC values, while models that included Phase as a random slope produced lower AIC values but failed to converge. Therefore, they were not included in the analysis. For comparison, a simpler model was included with Group, Phase, and their interaction as fixed effects. Using the same procedure to determine the best-fitting random effect structure, the model with Subject as a random intercept and Phase as a random slope produced the model with the lowest AIC value (AIC = 6433). Based on AIC values, the reduced model was the best-fitting model. The standard metric of $p < .05$ threshold was used for determining significance.

Results

A generalized mixed-effects model was used to predict the proportion of switching by Phase, Group, and their interaction. The best fitting model revealed that participants switched significantly less during Phase 1 but significantly more during Phase 2. The model also revealed a significant Group [Cont] x Phase [1] interaction (see Table 1).

Table 1

Parameter Estimates from Reduced Model

	Estimate	SE	*Z* value	Pr(>|z|)
Intercept	1.461	0.138	10.610	< 0.0001
Group [Cont]	-0.166	0.137	-1.216	0.224
Phase [1]	-0.401	0.083	-4.856	< 0.0001
Phase [2]	0.168	0.078	2.252	0.024
Group [Cont] * Phase [1]	0.227	0.080	2.851	0.004
Group [Cont] * Phase [2]	-0.103	0.068	1.514	0.130

Note. Estimates are shown as log-odds.

Figure 2 shows the mean percentage of switching for participants in the Experimental and Control groups. Post hoc analyses of all possible comparisons using Tukey's adjusted *p*-values revealed the proportion of switching in the Experimental group was significantly higher in Phase 2 ($z = -5.124$; $p < .0001$) and Phase 3 ($z = -4.621$; $p = .0001$) compared to Phase 1. All other pairwise comparisons were not significant ($p > .062$). These findings suggest that increasing the number of options available does improve performance independently of reinforcement probabilities. The results also suggest that these performance improvements persist despite reverting to three-option trials.

Figure 2

Percentage of Switching Across Phase
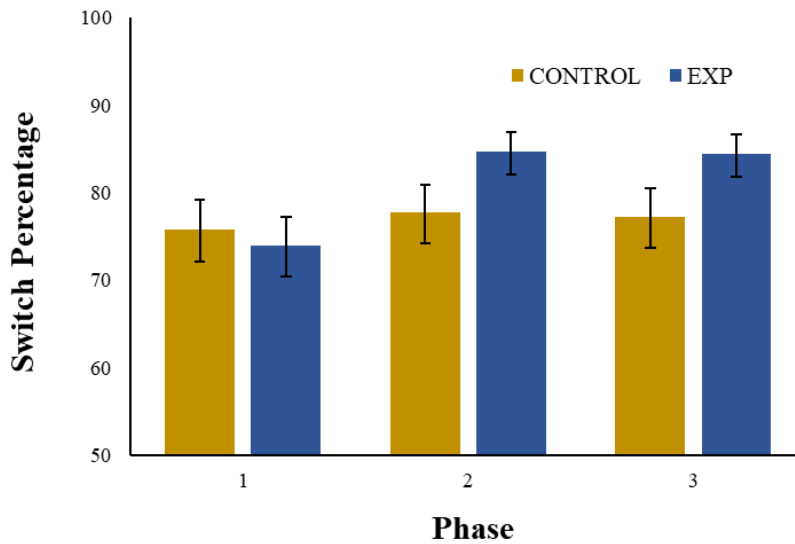
Note. Error bars represent ± 1 standard error.

Discussion

The results of the current study support the findings from prior studies that found that the addition of more options ultimately improved participants' performance (Burns & Weith, 2004; Franko-Watkins et al., 2003; Saenen et al., 2015; Stibel et al., 2009; Watzek et al., 2018). Our results show that performance differentially improved in the Experimental condition during Phase 2 when the number of available options increased to eight. This finding provides evidence that merely altering how the task is presented by introducing more options is sufficient to improve performance independently of changes in the reinforcement probabilities. Despite observing a significant improvement in performance from the Experimental condition, this improvement was moderate (approximately a 7% increase).

Including verbal instructions or increasing the number of available options for selection is not the only method to alter how the dilemma is potentially perceived. Tubau and Alonso (2003) changed how participants perceived the dilemma by allowing them to take the host's perspective before being tested as a contestant. The researchers found that the participants who took the host's perspective before testing switched significantly more than the control participants. Similar to the current study, the findings from Tubau and Alonso (2003) demonstrate that performance can be improved without changing the reinforcement probabilities.

A novel contribution of this study was eliminating reinforcement probabilities as a confound when the number of options were increased. Thus, these results suggest that the inclusion of more options without a commensurate increase in reinforcement probabilities was sufficient to increase switch rates compared to the Control condition. Furthermore, prior studies have shown that performance improved significantly when the probability of reinforcement was increased for switching without adding additional options for selection (Franco-Watkins et al., 2003; Herbranson & Schroeder, 2010; Hirao et al., 2016; Mazur & Kahlbaugh, 2012). These findings might suggest that reinforcement probabilities and number of options potentially interact to enhance performance.

Our findings expand on the results of Watzek et al. (2018), which explored whether humans could generalize their performance between two variations of the dilemma first demonstrated with capuchins and rhesus macaques. Watzek and colleagues hypothesized that including more options would improve performance and this improvement would persist when given an alternative version of the dilemma. The results from human participants supported their first hypothesis, but the participants did not generalize their performance from a non-verbal, experience-based computerized variation when tested on a description-based variation. Our results, however, showed that participants in the experimental condition behaved similarly to the capuchin monkeys in Watzek et al. (2018). The participants in the current study successfully generalized their previous experience with eight-option trials and continued to switch at significantly higher rates compared to the control condition, which did not experience eight-option trials.

This result may explain why performance generalization has been inconsistent in previous studies (Franko-Watkins et al., 2003; Watzek et al., 2018). Prior studies have assessed generalization by training participants using experience-based versions while testing them on single-trial, description-based variations. Participants in the current study and capuchin monkeys from Watzek and colleagues' (2018) study successfully demonstrated performance generalization when they were trained and tested on two experience-based variations of the dilemma.

Our results also indicate that the participants' switch rates in Phase 1 were higher than typically seen with experience-based Monty Hall tasks using repeated trials. We considered whether including the 'X' used to designate the selected option may have biased responding towards switching. However, this marker was included after any selection was made, including on winning trials. Ultimately, we suspect this difference may be due to natural variability in responding, rather than an effect driven by one or more procedural details.

The unusually high rates of switching observed in the participants of the current study, and the participants in Watzek and colleagues' (2018) study, can also be explained by the description-experience gap. The description-experience gap suggests that when relying on probabilistic reasoning, experienced-based methods involving multiple trials disproportionally engages working memory, attention, and other problem-solving processes while description-based methods primarily rely on heuristics and intuition (Schulze & Hertwig, 2021). Therefore, participants who are given description-based versions of the MHD may be more likely to rely on intuition when choosing, making generalization of their previous experience less likely. However, more research is needed to investigate the effects of differing contexts on performance and generalization in the MHD.

Results from the current study support that how probabilistic dilemmas are presented contributes to the level of accuracy that is assessed. Future research focused on reducing commonly committed errors within probabilistic dilemmas should explore how stimuli presentation can be modified to enhance the reinforcement outcomes associated with choice selections. The current study demonstrates that altering the presentation of the dilemma, thus influencing how the dilemma is potentially perceived, led to significant improvements in performance. This performance improvement also persisted when participants were returned to baseline conditions. More research is warranted to determine why performance generalization occurs in some contexts but not others. In addition, future research should examine how other manipulations to the presentation of probability-based dilemmas affects performance to better understand the factors that influence statistical intuitions.

Acknowledgments

References

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Bitterman, M. E. (1965). Phyletic differences in learning. *American Psychologist*, *20*(6), 396–410. https://doi.org/10.1037/h0022328

Boisgontier, M. P., & Cheval, B. (2016) The anova to mixed model transition. *Neuroscience & Biobehavioral Reviews,* *68*, 1004–1005. https://doi.org/10.1016/j.neubiorev.2016.05.034

Burns, B. D., & Wieth, M. (2004). The collider principle in causal reasoning: Why the Monty Hall dilemma is so hard. *Journal of Experimental Psychology: General*, *133*(3), 434–449. https://doi.org/10.1037/0096-3445.133.3.434

Efendić, E., & Drace, S. (2015). The influence of affect on suboptimal strategy choice in the Monty Hall dilemma. *Psychology, 48*(2), 135-147. https://doi.org/10.2298/PSI1502135E

Fantino, E., & Esfandiari, A. (2002). Probability matching: Encouraging optimal responding in humans. *Canadian Journal of Experimental Psychology*, *56*(1), 58–63. https://doi.org/10.1037/h0087385

Franco-Watkins, A. M., Derks, P. L., & Dougherty, M. R. P. (2003). Reasoning in the Monty Hall problem: Examining choice behaviour and probability judgements. *Thinking & Reasoning*, *9*(1), 67–90. https://doi.org/10.1080/13546780244000114

Gauvrit, N., & Morsanyi, K. (2014). The equiprobability bias from a mathematical and psychological perspective. *Advances in Cognitive Psychology*, *10*(4), 119–130. https://doi.org/10.5709/acp-0163-9

Granberg, D. (1999). Cross-cultural comparison of responses to the Monty Hall dilemma. *Social Behavioral and Personality*, *27*(4), 431–438. https://doi.org/10.2224/sbp.1999.27.4.431

Granberg, D., & Brown, T. A. (1995). The Monty Hall dilemma. *Personality and Social Psychology Bulletin*, *21*(7), 711–723. https://doi.org/10.1177/0146167295217006

Herbranson, W. T., & Schroeder, J. (2010). Are birds smarter than mathematicians? Pigeons (*Columba livia*) perform optimally on a version of the Monty Hall dilemma. *Journal of Comparative Psychology*, *124*(1), 1–13. https://doi.org/10.1037/a0017703

Herbranson, W. T., & Wang, S. (2014). Testing the limits of optimality: The effect of base rates in the Monty Hall dilemma. *Learning & Behavior*, *42*(1), 69–82. https://doi.org/10.3758/s13420-013-0126-6

Hirao, T., Murphy, T. I, & Masaki, H. (2017). Brain activities associated with learning of the Monty Hall Dilemma task. *Psychophysiology*, *54*(9), 1359–1369. https://doi.org/10.1111/psyp.12883

Iacobucci, D., Schneider, M. J., Popovich, D. L., & Bakamitsos, G. A. (2016). Mean centering helps alleviate "micro" but not "macro" multicollinearity. *Behavior Research Methods*, *48*(4), 1308–1317. https://doi.org/10.3758/s13428-015-0624-x

Klein, E. D., Evans, T. A., Schultz, N. B., & Beran, M. J. (2013). Learning how to "make a deal": Human (*Homo sapiens*) and monkey (*Macaca mulatta*) performance when repeatedly faced with the Monty Hall Dilemma. *Journal of Comparative Psychology*, *127*(1), 103–108. https://doi.org/10.1037/a0029057

Krauss, S., & Wang, X. T. (2003). The psychology of the Monty Hall problem: Discovering psychological mechanisms for solving a tenacious brain teaser. *Journal of Experimental Psychology: General*, *132*(1), 3–22. https://doi.org/10.1037/0096-3445.132.1.3

Lenth, R. (2022). _emmeans: Estimated Marginal Means, aka Least-Squares Means. R package version 1.8.3, https://CRAN.R-project.org/package=emmeans.

Mazur, J. E., & Kahlbaugh, P. E. (2012). Choice behavior of pigeons (*Columba livia*), college students, and preschool children (*Homo sapiens*) in the Monty Hall Dilemma. *Journal of Comparative Psychology*, *126*(4), 407–420. https://doi.org/10.1037/a0028273

Petrocelli, J. V., & Harris, A. K. (2011). Learning inhibition in the Monty Hall problem: The role of dysfunctional counterfactual prescriptions. *Personality and Social Psychology Bulletin*, *37*(10), 1297–1311. https://doi.org/10.1177/0146167211410245

Saenen, L., Heyvaert, M., Van Dooren, W., & Onghena, P. (2015). Inhibitory control in a notorious brain teaser: The Monty Hall dilemma. *ZDM Mathematics Education*, *47*, 837–848. https://doi.org/10.1007/s11858-015-0667-6

Saenen, L., Heyvaert, M., Van Dooren, W., Schaeken, W., & Onghena, P. (2018). Why humans fail in solving the Monty Hall Dilemma: A systematic review. *Psychologica Belgica*, *58*(1), 128–158. https://doi.org/10.5334/pb.274

Schulze, C., & Hertwig, R. (2021). A description–experience gap in statistical intuitions: Of smart babies, risk-savvy chimps, intuitive statisticians, and stupid grown-ups. *Cognition*, *210, 1-16*. https://doi.org/10.1016/j.cognition.2020.104580

Sousa, D. A. (2016). *How the brain learns*. Corwin Press.

Stagner, J., & Zentall, T. (2014). Further investigation of the Monty Hall Dilemma in pigeons and rats. *Behavioral Processes*, *112*, 14–21. https://doi.org/10.1016/j.beproc.2014.10.008

Stibel, J. M., Dror, I. E., & Ben-Zeev, T. (2009). The collapsing choice theory: Dissociating choice and judgment in decision making. *Theory and Decision*, *66*, 149–179. https://doi.org/10.1007/s11238-007-9094-7

Tubau, E., & Alonso, D. (2003). Overcoming illusory inferences in a probabilistic counterintuitive problem: The role of explicit representations. *Memory & Cognition*, *31*(4), 596-607. https://doi.org/10.3758/BF03196100

Vulkan, N. (2000). An economist's perspective on probability matching. *Journal of Economic Surveys*, *14*(1), 101-118. https://doi.org/10.1111/1467-6419.00106

Watzek, J., Whitham, W., Washburn, D. A, & Brosnan, S. F. (2018). Responses to modified Monty Hall Dilemmas in capuchin monkeys, rhesus macaques, and humans. *International Journal of Comparative Psychology*, *31*, 1-16. https://doi.org/10.46867/ijcp.2018.31.03.06

Young, M. E. (2018). Discounting: A practical guide to multilevel analysis of choice data. *Journal of Experimental Analysis of Behav*ior, *109*(2), 293–312, https://doi.org/10.1002/jeab.316

Zentall, T. R., Case, J. P., & Collins, T. L. (2015). The Monty Hall Dilemma with pigeons: No, you choose for me. *Learning Behavior*, *43*, 209–216. https://doi.org/10.3758/s13420-015-0172-3