



Probability Discounting in College Students' Willingness to Isolate During COVID-19: Implications for Behavior Analysis and Public Health

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Abstract

The present study was a preliminary analysis of college students' willingness to self-isolate and socially isolate during the COVID-19 pandemic analyzed through a probability discounting framework. Researchers developed a pandemic likelihood discounting task where willingness to isolate from others was measured in days as a function of the perceived probability of the escalation of a virus to pandemic levels. Experiment 1 was conducted immediately prior to the World Health Organization (WHO) declaring COVID-19 a pandemic and results showed that participants were more willing to self-isolate when the perceived probability of reaching pandemic levels was high and when there was a guarantee that others in the community would do the same. Experiment 2 was conducted with a subset of participants from Experiment 1 with the same discounting task, and results showed that participants were more willing to self-isolate 2 months following the onset of the pandemic, supporting the view that willingness to isolate from others is a dynamic process. Finally, Experiment 3 evaluated willingness to socially distance and introduced a hypothetical timescale to evaluate common trends with the real-world temporal dynamics observed in Experiments 1 and 2. Results showed similar trends in the data, supporting the use of hypothetical scenarios within probability discounting tasks in future behavior analytic research related to public health.

Keywords COVID-19 · probability discounting · public health · social isolating

Coronavirus Disease 2019 (COVID-19; Centers for Disease Control & Prevention [CDC], 2020; World Health Organization [WHO], 2020) is a respiratory disease that is spread through respiratory droplets produced when a person sneezes, coughs, or talks. COVID-19 was originally reported to the WHO on December 31, 2019, and on January 30, 2020, the WHO declared COVID-19 a global public health emergency. COVID-19 was officially declared a global pandemic on March 11, 2020. Epidemiologists immediately began researching the transmissibility and spread of the virus and recommended several public health measures, such as wearing facemasks, disinfecting surfaces, and socially distancing or isolating whenever possible (Mann et al., 2020). Public health recommendations were made concurrently with the development of vaccinations to curb the spread of COVID-19 or similar widespread viral diseases

while the public awaited widescale vaccine availability (Corey et al., 2020).

As of February 2021, there were over 26 million confirmed cases and over 500,000 confirmed deaths in the United States alone. Recent experimental evidence suggests that a number of factors may influence decision making as it pertains to risk with potential translation to understanding individual choices made during the pandemic. For example, Jiang and Dai (2021) manipulated perceived risk of receiving a larger-later sum of money and showed that greater perceived risk was predictive of higher levels of delay discounting (i.e., a pattern of choosing smaller-sooner reinforcers over larger-later reinforcers). Events occurring during the pandemic that could have downplayed risk could therefore operate as contextual events influencing suboptimal group decision making in times of public health crises. For example, in the United States, then President Donald Trump stated in an interview, "I always wanted to play it down. I still like playing it down . . . because I don't want to create a panic" (Keith, 2020). Although causal claims are not possible from this or other political statements made during this

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time, downplaying the progression of COVID-19 could operate as a contextual factor influencing the adoption of public health measures that may be one of many contributions behavior scientists could make to this area of applied research.

As noted by Hayes et al. (2020),

Despite the extraordinary breadth of impact of the pandemic it is worth noticing that the behavioral sciences are barely visible in the public or policy discussions. Instead, behavior change advice is being doled out in a common-sense way. This can and does work in some cases, but without behavioral scientists' involvement, there is no fall back when public health information alone is not enough. (p. 128)

The authors go on to advocate for the inclusion of behavior scientists in three primary domains related to public health crises such as COVID-19, including: (1) interventions designed to minimize suffering due to trauma; (2) interventions designed to protect against burnout of essential workers; and (3) advocating for scientifically supported public health policies that can influence health-related behavior.

Research on the first and second areas has been forthcoming both within and outside of behavior analytic journals (e.g., Coyne et al., 2021; Szabo et al., 2020); however, research on behavior change mechanisms that may contribute to people's willingness to adopt policies that promote public health has been more limited. One reason may be that data may be difficult to capture in the moment of the public health crisis, because events such as the COVID-19 pandemic occur approximately once per century (Javelle & Raoult, 2021). A method is needed through which to generate data about public health policies and people's willingness to take preventative measures to curb spread and transmission. In so doing, behavior analysts may have data to contribute above and beyond "common sense measures" (see above quote from Hayes et al., 2020) that can inform scientifically supported public health strategies.

Hypothetical tasks or questionnaires designed from within a behavioral economic framework emphasizing delay or probability discounting processes could have utility in generating relatively large datasets quickly that could provide information informing future public health policy development. Discounting processes refer to a decay in the subjective value of a reward across a measurable dimension such as delay to receiving the reward (i.e., delay discounting) or decreased likelihood of receiving the reward (i.e., probability discounting) (McKerchar & Renda, 2012) with implications for understanding choices during public health crises. For example, Hursh et al. (2020) evaluated the probability that people would accept vaccinations for COVID-19 using hypothetical vaccination scenarios. Similar discounting tasks in other areas of public health such as

sexual activity and substance use (Heckman et al., 2019; Hursh & Roma, 2013; Strickland et al., 2020).

Behavior analysts may contribute to an even greater extent by isolating contextual (i.e., environmental) factors that influence discounting and choice at the onset of potential pandemic events. An original study by Ostaszewski et al. (1998) demonstrated that delay and probability discounting can be influenced by quasi-experimental inflation as a quasi-experimental contextual variable. High rates of currency inflation in Poland in years prior to 1994 led to depreciation of the *zloty* relative to the U.S. dollar. In a series of two experiments, the researchers established that the subjective value of a delayed or probabilistic reward was less when the amount was specified in old *zlotys* compared to dollars. In a third experiment, which occurred after the introduction of a new and more stable *zloty* (i.e., less affected by inflation) in 1995, the same outcome was not observed.

Harman (2021) evaluated how the framing of time would affect people's willingness to social isolate during a pandemic across various delay values. The delay was framed as either calendar units (e.g., days or weeks) or specific dates at which distancing policies would be lifted (e.g., September 10, 2020). Results suggested that time framed in units supported steeper discounting rates and self-identified conservative participants demonstrated overall greater discounting compared to self-identified liberal participants in the study. Plumm et al. (2012) conducted a similar study within a delay discounting framework promoting equal rights across multiple policy domains. Public policies were framed as either affirmative action policies or as policies to promote equal rights for all citizens, where results suggested that steeper discounting was observed when policies were framed as promoting affirmative action.

This strategy is highly compatible with a process-based approach to behavioral intervention advocated for by Hayes et al. (2020) in the context of COVID-19. In particular, behavior change strategies should be grounded in a well-defined behavior analytic theory of change. Discounting models provide a quantitative model that emphasizes relative rates of reinforcement as a function of contextual factors such as delay or probability (Madden et al., 1999). Strategies should capture dynamic changes in behavior in response to the environment. This data could theoretically be captured by monitoring changes in public health policy preference throughout the progression of a public health crisis. Behaviors should be contextually bound and modifiable. The research on framing suggests that factors external to the policy parameters could influence policy preferences, and the rapid data collection method could provide opportunities for other experimental manipulations. Finally, solutions should occur at multiple levels of analysis (Hayes et al., 2021).

A major limitation of these studies is that the scenarios were not presented throughout the public health crisis, so it is

unknown how choices evolve dynamically or are influenced by events such as COVID-19. Although prior research has supported convergence between hypothetical responses within a monetary discounting task and actual decision making (e.g., Madden et al., 2003), an extrapolation of this relationship to data relating to public health policies cannot necessarily be assumed. Such relationship must be established to support a dynamic model that can predict and influence public health choices. Second, framing is not likely the only parameter that can influence people's willingness to adopt preventative public health measures, such as social distancing. Choices related to public health are complex and involve social contingencies that likely interact at multiple levels (Hayes et al., 2020; Normand et al., 2021). For example, if an individual elects to socially isolate for a set duration, there is no guarantee that others will also choose to socially isolate, minimizing the collective benefit arising from preventative choices of individuals. This is represented in choice-based research stemming from the prisoner's dilemma (Rapoport et al., 1965), where choices that benefit individuals may harm the group and as a result limit the benefits that could be realized through collective action (Rogowski & Lange, 2020; Thürmer et al., 2020). Group contingencies have also been shown to influence delay discounting processes (Bixter & Luhman, 2020).

The purpose of the present study was to conduct a series of experiments that took place throughout the COVID-19 pandemic to illustrate the dynamic evolution of choices during the pandemic and to evaluate the convergence between hypothetical scenarios and patterns of responding during the public health crisis. In addition, researchers sought to evaluate how the perceived probability of a global pandemic and individual versus collectivistic framing influenced public health policy preference. The first two experiments provide a quasi-experimental analysis of the effect of time and the progression of COVID-19 as another contextual factor. In the third study, a similar pandemic likelihood discounting task was developed with hypothetical framing of time to determine if hypothetical choices resembled the choice dynamics observed in the prior two studies. It should also be noted that given the time at which the present studies were conducted, language was shifting regarding the pandemic as well as the precautionary measures of such. For the purpose of these studies, the term "self-isolating" will be used as an interchangeable term to previously be referred to "social distancing" and "distancing."

General Methods (Experiments 1–3)

Participants and Setting

Two independent convenience samples were recruited for the purposes of the present study. The same sample participated

in Experiments 1 and 2 and a new sample was recruited for Experiment 3. Participants were recruited from undergraduate college credit courses at a midwestern American university in the psychology department. All of the participants attended the university in person in the state of Missouri. Given the age range of the participants, the sample represented a low-risk group for long-term effects or death resultant from the virus as was made evident as more information was obtained about COVID-19 throughout the study. Students were offered five extra credit points in their course for completing this first phase of the research study. The study was completed in class led by one of the researchers who described the study, obtained participant consent, and administered the link to complete the demographics questionnaire and the pandemic likelihood discounting task designed for the purposes of this study. Students completed the demographic survey and the discounting tasks through any available accessible technology device (e.g., laptop, cellular device, tablet) of their choice. Participants were also given the option to complete a paper version of the survey and pandemic likelihood discounting task; however, all participants elected to use their phone, laptop, or tablet device.

The materials utilized for the study were formatted in Qualtrics (Qualtrics, Provo, UT), an online survey software tool that was used to design and distribute the materials. Participant confidentiality was maintained by programming the Qualtrics study to separate participant names (for extra credit purposes) from their survey responses. The consent form and the demographic questions were presented at the onset of the survey, followed by a series of pandemic discounting tasks. The pandemic discounting tasks were identical in Experiments 1 and 2, where participants completed the discounting task under an individual contingency and a group contingency. The second experiment was conducted to determine how the progression of the pandemic over time influenced responding of the same participants from Time 1 to Time 2.

All participants were provided a statement that read:

Coronavirus 19 (COVID-19) is becoming a concern in the United States. COVID-19 is a viral illness that ranges in mild symptoms to severe illness and death. Symptoms may include fever, cough, and shortness of breath and is spread by coming in contact with small droplets from an infected person's nose or mouth by coughing or exhaling. As of March 9, 2020, the reported amount of confirmed cases in the United States was 213 with 11 deaths. The World Health Organization reported "now that the virus has a foothold in so many countries, the threat of a pandemic has become very real." The definition of a pandemic is defined as "an outbreak of a disease that occurs over a wide geographic area and affects an exceptionally

high proportion of the population.” One solution is for people to self isolate (i.e., avoid public places) until the spread of the virus decreases to near zero rates. In the current survey, assume that food, shelter, and financial stability are provided for the duration of the isolation period.

The sequence of the pandemic likelihood discounting tasks was randomized across the participants to control for potential sequence effects, where half of the participants completed the individual-contingency task first and the other half completed the group-contingency task first. In both tasks, participants were first provided information about the task followed by a series of concurrent choices between distancing from others for a period of time to avoid a pandemic or not social distancing with a probability of COVID-19 becoming a pandemic. In the individual-contingency condition, the participants were given the following information: “DO NOT ASSUME that every other person will make the same decision that you do, so the success of prolonged isolation from others may be less effective if fewer people make the same decision you do.” In the group-contingency condition, the participants were given the following information: “ASSUME that every other person will make the same decision that you do, so the success of prolonged isolation from others may be more effective at avoiding a pandemic.”

The concurrent choices were identical in both discounting tasks, where the only difference was the description of individual versus group behavior. The concurrent choice questions took the form of:

Option A: Self-isolate for 0 Days, Y% chance of pandemic in U.S.

OR

Option B: Self-isolate for X days, 0% chance of pandemic in U.S.

There were 70 concurrent choices within each pandemic likelihood discounting task (for a total of 140 choices per participant). X was the number of days the participants would be willing to self-isolate ranging from 0 to 30 days (e.g., 3, 6, 9, 12, 15, 18, 21, 24, 27, 30 days). Y was the titrations of the percent for the pandemic (e.g., 2.5%, 5%, 10%, 15%, 25%, 35%, 50%). Participants were given a total of 20 min to complete the pandemic likelihood discounting tasks.

The third experiment revised the discounting task to include a hypothetical time frame to determine if similar temporal dynamics could be observed in this arrangement. The survey was adapted based on new information about COVID-19 and prevention measures that were not known at the time that the initial survey was administered.

In particular, it was learned that social distancing (i.e., holding small group outdoor events) could achieve similar prevention to the initial recommendations of self-isolating (i.e., remaining indoors and without contact) at the beginning of the pandemic (CDC, 2020). The incubation period of the virus was also approximately 2 weeks (Lauer et al., 2020), providing an estimate of the minimum duration of social distancing or isolating that would be required to slow the spread of COVID-19.

Dependent Variable and Analysis

The dependent variable for all three experiments was the duration, in days, that participants were willing to self-isolate or socially distance across the different perceived probability of COVID-19 becoming a pandemic within each of the conditions (i.e., individual contingency or group contingency). Indifference points for each probability value were calculated by determining the median value where participants switched from selecting Option B (self-isolate for X days) to selecting Option A (self-isolate for 0 days, with a chance of pandemic).

To evaluate the discounting function and consistent with previous research, the probability of pandemic was converted to “odds-against pandemic” by subtracting the probability of pandemic (p) from 100 and dividing this value by the probability value (i.e., $(100-p)/p$) as described by Rachlin et al. (1991). The converted odds-against values were used as the primary predictor variable across all analyses in the current study.

At this stage of the experiment, participants were excluded if they engaged in exclusive selection of either option A or option B to reduce the influence of ceiling or floor effects on the data analysis. Participants were also excluded if they did not answer all questions in the discounting task or switched more than once within a probability value (i.e., a switch point could not be determined). To determine if the results were consistent with hyperbolic discounting models shown in prior work on probability discounting, the following discounting equation was fit to the obtained average indifference values across each condition based on Rachlin et al. (1991) probability discounting model:

$$v = \frac{A}{(1 + h\theta)} \quad (1)$$

Where v is the subjective value of the probabilistic reward (i.e., estimated indifference point), A is the maximum value (i.e., undiscounted value, 31.5 days of isolation in Experiments 1 and 2 and 62.5 in Experiment 3), θ is the odds-against the pandemic, and h is a parameter

that reflects the discounting rate. The goodness of fit was evaluated for the hyperbolic equation using Statistica software (Tibco Software Inc., 2014).

Researchers also evaluated if the addition of another parameter s would improve the fit consistent with Ostaszewski et al. (1998) hyperboloid function for probability discounting:

$$v = \frac{A}{(1 + h\theta)^s} \tag{2}$$

where s is a nonlinear scaling parameter of odds-against that is generally equal to or less than 1.0 (McKerchar et al., 2010). Because the current study involved a novel discounting task for the present experiment, an R^2 values ≥ 0.90 was considered indicative of a strong fit that would suggest discounting in a pandemic context resembles discounting as a broader behavioral phenomenon.

Responses across conditions were then compared using area under the curve (AUC) as an atheoretical model of discounting. AUC compares the space under the curve as an estimate of discounting, where lower values are indicative of steeper discounting. AUC was calculated using the formula (Myerson et al., 2001):

$$AUC = \sum (x_2 - x_1) \left[\frac{(y_1 + y_2)}{2} \right] \tag{3}$$

Where x_1 and x_2 represent successive proportional odd-against values, y_1 and y_2 are the subjective values associated with the odds-against values, and \sum represents the sum of each trapezoid calculated using the contained formula.

Experiment 1: Initial Task Administration

Participants and Procedures

A total of 42 participants took part in Experiment 1 and 39 (26 female, 13 male) were retained based on the initial exclusion criteria in the data analysis phase (described below). The age of the retained participants ranged from 19 to 32 ($M = 21.6$ years; $SD = 1.2$ years). Of the 42 participants, 30 identified as leaning politically democratic, 9 identified as having no differential political leaning, and 3 identified as leaning politically republican. No information was obtained regarding participants' personal or family income. Researchers utilized a repeated measures research design where all participants experienced the individual and group-based pandemic likelihood discounting tasks in a randomized sequence. The average time to complete the discounting tasks was 15.4 min.

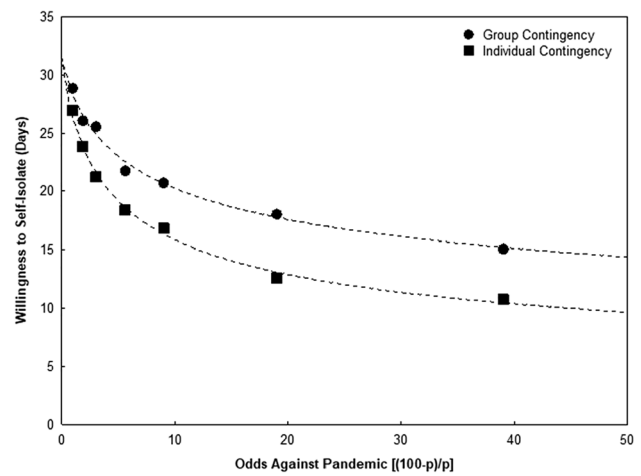


Fig. 1 Mean Indifference Point Data (Willingness to Self-Isolate) across the Two Experimental Conditions. Note. Discounting curves were estimated using the hyperboloid curve function (Eq. 2)

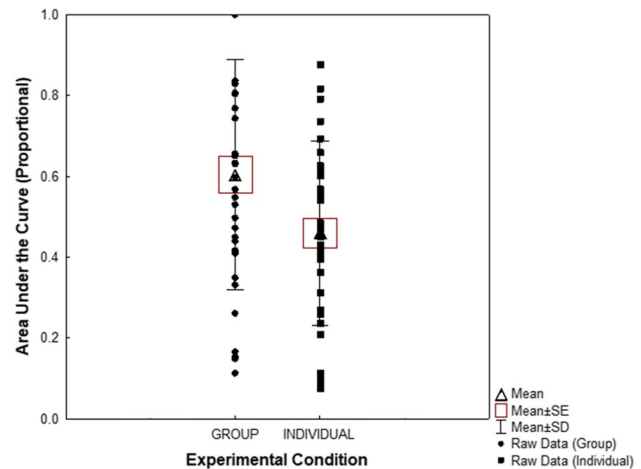


Fig. 2 Jittered Box and Whisker Plot of AUC Values across the Two Experimental Conditions. Note. Raw data points for each participants are displayed in the plot. Mean values are represented by triangles and standard error (box) and standard deviation (whisker) are shown in the plot

Results and Discussion

The results of Experiment 1 are summarized in Figs. 1 and 2. Figure 1 shows the mean willingness to self-isolate in days (indifference point) as a function of the odds-against pandemic. Visual analysis shows steeper rates of pandemic likelihood discounting in the individual condition relative to the group condition, suggesting participants were more willing to self-isolate for a longer duration given the group contingency. Model fits for both the hyperbolic model (Eq. 1) and the hyperboloid model (Eq. 2) were compared using the extra sum of squares F test, where the hyperbolic model

represented the more parsimonious model due to fewer free parameters. For the individual contingency, the results supported that the hyperboloid model was the preferred model ($F(1, 5) = 191.5, p < 0.01$) generating an R^2 of 0.99 that also exceeded the $R^2 \leq 0.90$ threshold. Results also supported the hyperboloid model as the preferred model for the group contingency ($F(1, 5) = 142.6, p < 0.01$) generating an R^2 of 0.99. The curve fit analysis in the figure was completed using a nonlinear least square model estimation with a Levenberg-Marquardy estimation method using the hyperboloid model. Obtained h and s values also support greater mean discounting rates in the individual condition, producing values of 0.58 (h) and 0.23 (s) in the group contingency and 0.70 (h) and 0.33 (s) in the individual contingency. The greater s value in the equation supports the visual conclusion that steeper discounting was observed in the individual contingency condition.

Taken together, these results suggests that participants may be discounting the probability of viral infections spreading to pandemic levels similar to probability discounting of monetary gains and losses in both experimental conditions. The group contingency, however, resulted in an average greater willingness to self-isolate for 3.63 days (i.e., 0.5 weeks). This amount of time is potentially socially significant at a time where the incubation period of the virus was not well-known, and the progression of the virus not easily predicted by the respondents in the pandemic likelihood discounting task. For example, had observed control measures been adopted at scale in the United States 1 week earlier (i.e., March 8, 2020, instead of March 15, 2020), Pei et al. (2020) estimated that there would have been 32,335 fewer deaths as of May 3, 2020, in the United States.

AUC values were obtained to allow for comparison between the two conditions and are shown in Fig. 2 in a jittered box and whisker plot. AUC values range from 0.0 to 1.0 and represent the proportional area under the curve for each participant. The mean AUC for group contingency was 0.604 (range: 0.11–1.0; $SD = 0.28$) and for the individual contingency was 0.459 (range: 0.08–0.88; $SD = 0.23$). The mean data and visual analysis as shown in the figure support the general conclusion that greater discounting was observed in the individual condition compared to the group condition; however, visual analysis of the raw data as well as the SD values suggest that the data were highly variable across participants.

High variability can make visual analysis of the data alone difficult to interpret. To further analyze the data, a series of statistical tests were conducted. First, a Shapiro-Wilk test for normality was conducted, where p -values less than 0.05 represent a significant deviation from a normal distribution. Results suggested that although the data from the individual condition were normally distributed ($p = 0.31$); however, the data from the group contingency were

not normally distributed ($p = 0.02$). Because one of the variables was not normally distributed, a nonparametric comparison of the obtained AUC values across the two groups was conducted. A Wilcoxon Signed-Ranks test indicated that AUC scores in the group condition were greater than the individual condition, $Z = 3.53, p < 0.01$.

The effect size difference between the two conditions using Cohen's d (Cohen, 1988) within subjects equation using the descriptive statistics described below along with an obtained Pearson's correlation coefficient between the conditions of $r = 0.69$ was also evaluated. Results of the effect size analysis produced an effect size of $d = 0.69$, which is just below the threshold for a large effect size ($d \geq 0.70$). Given the exploratory nature of this study, a power analysis using the obtained effect size was also conducted to guide future evaluations extending upon this study. The power analysis was conducted using G*Power 3.1 statistical software. The stated test was the Wilcoxon Signed Ranks two-tailed test as was conducted in the present study. The alpha error rate was set to 0.05 and power was set to 0.95. Results suggested that future analyses evaluating differences across experimental conditions should contain an estimated sample size of $N = 31$. Despite limitations (refer to general discussion), these initial results do suggest that probability discounting may be orderly and sensitive to context variables, such as group or individual contingencies, providing an avenue for future research for behavior scientists.

In the second experiment, researchers wanted to evaluate if participant responses changed 2 months following the WHO declaring COVID-19 a global pandemic (Sohrabi et al., 2020). Several events had transpired during this time and, because of the sample, similar changes were experienced by the sample such as on-campus class closures and statewide closures of nonessential businesses. Therefore, this second experiment provided a snapshot of changes in pandemic discounting over the naturally occurring timespan of COVID-19 for these student participants.

Experiment 2: Follow-Up Task Administration

Participants and Procedures

Of the original 39 participants that were retained in the Experiment 1 analyses, 23 consented to participate in the second administration of the study where they were provided with another pandemic likelihood task. The second test administration was conducted later in the semester on May 9 and 10, or 2 months following the initial administration of the delay pandemic likelihood discounting task. At this point in time, the WHO had declared COVID-19 a global pandemic. All students had transitioned to exclusively

online or remote learning due to university-wide on-campus classroom closures. At this time (May 9), there were 1,298,956 confirmed cases in the United States and 78,786 deaths (CDC, 2022). Because of on-campus closures, the second administration of the survey was completed remotely over Zoom during the designated classroom period.

Pandemic likelihood discounting tasks were identical to those used in Experiment 1, except that the date, number of COVID-19 cases, and number of deaths were adjusted to match the total value as of May 9, 2020. The sequence of the discounting task was randomized, and the initial experimental order was not adjusted for. A 2x2 ANOVA was conducted that produces main effects for each independent variable (time and condition) and their interaction. It is important to note that because of the smaller sample size due to attrition that the probability of a Type 2 error is high using an alpha of 0.05 as a decision-making threshold. Therefore, the results of the statistical analysis should be used to guide future research and as supplementary to the curve-fit analysis as the main analytic strategy.

Results and Discussion

Figure 3 shows the mean indifference point data across both the individual (square) and the group (circle) contingency conditions and at the two different points in time (T1, closed symbol; T2, open symbol). Visual analysis of the data again support a difference between the two conditions, where steeper discounting appeared to occur in the individual conditions both at Time 1 and at Time 2. Within both conditions, steeper discounting is also apparent at Time 1 relative to Time 2, where greater willingness to self-isolate is apparent during the second measurement period. As in

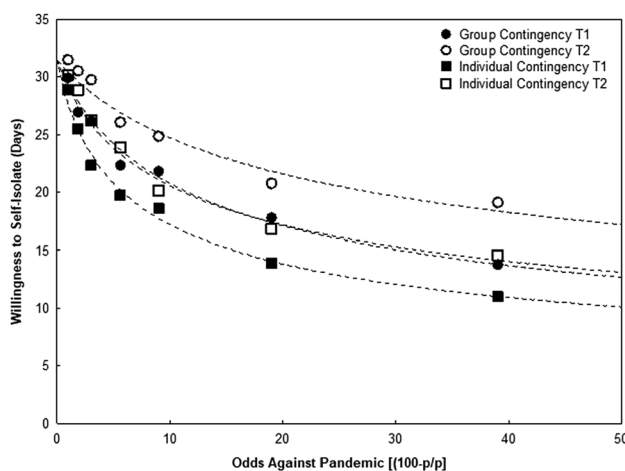


Fig. 3 Mean Indifference Point Data (Willingness to Self-Isolate) across the Two Experimental Conditions and at Two Different Points in Time. *Note.* Discounting curves were again estimated using the hyperboloid curve function (Eq. 2).

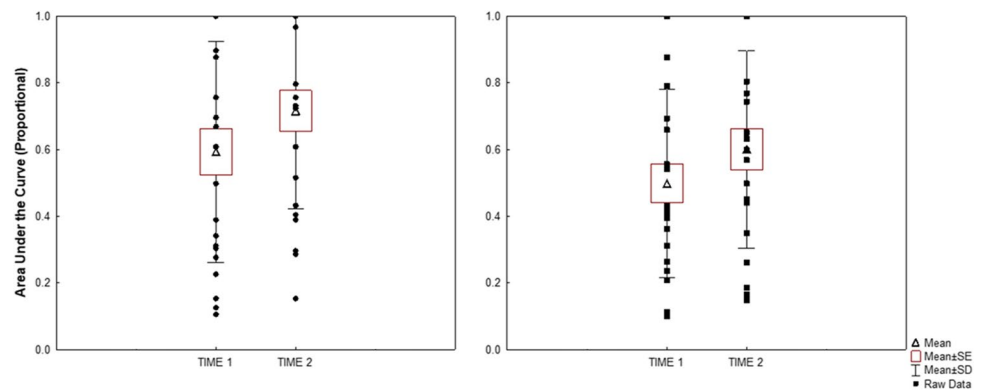
Experiment 1, hyperbolic and the hyperboloid models were compared using the extra sum of squares F test. For the individual contingency condition, the hyperboloid model provided the preferred fit at Time 1 ($F(1, 5) = 40.59, p < 0.01$) and at Time 2 ($F(1, 5) = 19.29, p < 0.01$). Both curves generated R^2 values of 0.99 and 0.98, respectively with parameter estimates at Time 1 of $h = 0.41, s = 0.37$; and at Time 2 of $h = 0.19, s = 0.38$, where the h parameter appeared to drive steeper discounting at Time 1 relative to Time 2. For the group contingency condition at Time 1, the hyperboloid model provided the preferred fit at Time 1 ($F(1, 5) = 31.96, p < 0.01$); however, at Time 2, the hyperbolic model provided the preferred fit ($F(1, 5) = 6.55, p = 0.05$) although this model comparison was approaching statistical significance. Because the other analyses were best fit by the hyperboloid model, each condition was evaluated using this function for subsequent analyses. Both curves generated R^2 values of 0.98 and 0.96, respectively. Best fit parameter estimates at Time 1 were $h = 0.26, s = 0.33$; and at Time 2 were $h = 0.11, s = 0.32$. Again, steeper discounting at Time 1 appeared to be driven by the greater h value. All hyperboloid models exceeded the $R^2 \geq 0.90$ threshold.

AUC data across Time 1 and Time 2 administrations are summarized in Fig. 4 for both conditions. For the group condition, the mean AUC was 0.59 at Time 1 and 0.72 at Time 2. Like in Experiment 1, visual and descriptive analyses suggest that the data were highly variable across participants at Time 1 (range: 0.11–1.0; $SD = 0.33$) and Time 2 (range: 0.15–1.0; $SD = 0.29$). For the individual condition, the mean AUC was 0.50 at Time 1 and 0.60 at Time 2. Like with the group data, differences in means between the times suggest that discounting was greater at Time 1 compared to Time 2. The data were also highly variable across participants at Time 1 (range: 0.10–1.0; $SD = 0.28$) and Time 2 (range: 0.15–1.0; $SD = 0.30$).

Again, variability in the data make it difficult to interpret visually. The results of the 2x2 ANOVA did not support statistically significant findings with an alpha level of 0.05 as anticipated, but results were approaching this threshold suggesting more research may be necessary to further evaluate this outcome. The main effect of time produced a F value of 3.23 and $p = 0.08$ and the main effect of the condition produced an F value of 2.78 and $p = 0.10$. There did not appear to be an interaction effect between the two variables ($p = 0.86$).

Although the results were not statistically significant, it is important to note that the sample size was smaller than in Experiment 1. Because time was the independent variable that may have had the greatest effect, this variable was used to estimate the required sample size for future analyses. The effect size was calculated at $d = 0.38$ for the group contingency and $d = 0.46$ for the individual contingency using the same within-subject analysis as in Experiment 1 and

Fig. 4 Jittered Box and Whisker Plot of AUC Values across Time 1 and Time 2 in the Group Contingency (Left) and the Individual Contingency (Right) Conditions. *Note.* Raw data points for each participants are displayed in the plot. Mean values are represented by triangles and standard error (box) and standard deviation (whisker) are shown in the plot



correlation coefficients of $r = 0.46$ and $r = 0.70$, respectively. The effect size for both conditions across time represents a medium effect size and is lower than in the previous experiment, suggesting that the statistical interpretation may represent a Type 2 error (i.e., false negative) given the proximity of both p values to the 0.05 threshold. According to a subsequent post-hoc power analysis using the same procedure as in Experiment 1 for both conditions across time, it is estimated that a sample size ranging from 68 to 98 participants would be needed in future analyses to avoid this error.

As mentioned above, the prior research suggests that the participants may be discounting the probability of the pandemic worsening similar to probability discounting of momentary wins and losses. Resulting in participants to agree to isolate for longer periods of time in Group 2. Similar to Study 1, the group contingency resulted in a greater willingness to isolate for an additional 3.4 days at Time 2 compared to Time 1; and in the individual group, for an additional 2.9 days at Time 2 compared to Time 1. Like with the previous studies, the impact of a few days can be considerable when considered at a national or international scale and at the level of whole populations. A good fit for the hyperbolic relationship was also observed, which diverges from the results observed in Experiment 1. Differences include the number of subjects as well as the location of the experiment due to COVID-19 and campus closures, but it is impossible to isolate this effect given the quasi-experimental design.

In the third and final experiment, researchers attempted to evaluate the responses of a similar pandemic likelihood discounting task given to a different set of participants, but this time using a hypothetical time scale. Researchers cannot simply go back in time to obtain new samples to evaluate real-time contextual conditions that influence pandemic likelihood discounting; however, it can be evaluated if similar patterns are evident when the passage of time as a hypothetical independent variable are introduced. If similar patterns are observed, this provides some confirmation that results obtained in similar tasks can identify trends that correspond to real-world phenomena. Moreover, if a

significant difference is observed in the same direction (i.e., past results in greater discounting than in the present), this could provide some support that the statistical analysis in Experiment 2 represents a Type 2 error and the passage of time confounded with the worsening of the pandemic may influence probability discounting.

Experiment 3: Hypothetical Timescale Administration

Participants and Procedures

A total of 38 participants enrolled in the same courses as the previous sample in a different semester took part in Experiment 3 and 34 were retained based on the same retention criteria. The task adapted to present a hypothetical time scale to simulate the passage of time variable from the prior study, where participants would “think back” 5 months prior to the present day and complete the survey based on how they would have responded then. This was done to evaluate if a similar influence of time could be captured using hypothetical time scales to inform future research.

After completing basic demographic questions, the participants were provided with the following statement:

Coronavirus (COVID-19) is a pandemic that is affecting families in the United States and across the world. COVID-19 is a viral illness that ranges in mild symptoms to severe illness and death; symptoms may include fever, cough, and shortness of breath and is spread by coming in contact with small droplets from an infected person’s nose or mouth by coughing or exhaling. As of September 7th, 2020, the reported confirmed cases in the United States was 6,189,488 with 187,541 deaths. The definition of a pandemic is defined as “an outbreak of a disease that occurs over a wide geographic area and affects an exceptionally high proportion of the population.” One solution is for people to socially distance (i.e.,

avoid public places and maintain 6-feet of distance from others in social settings) until the spread of the virus decreases to zero rates. In the current survey, assume that food, shelter, and financial stability are ensured for the duration of social distancing. Failure to socially distance could prolong the pandemic, leading to a greater number of cases, deaths, and social restrictions for a longer duration of time.

ASSUME that every other person will make the same decision that you do, so the success of social distancing is likely to be effective at avoiding a pandemic.

After reading this statement the participants were presented with past, present, and future scenarios from which to answer the pandemic likelihood discounting concurrent choices. The hypothetical timescale scenarios were developed to encourage participants to respond as if they were completing the task at a different point in time. This type of response likely involves deictic and temporal relational framing of then versus now and the timescale sequence. The scenarios were randomly sequenced and presented prior to each pandemic likelihood discounting task to control for potential sequence effects. The hypothetical timescale also allowed for an experimental analysis of the effect of time, rather than a quasi-experimental analysis as was completed in Experiment 2 in comparison to Experiment 1. The scenarios were:

Scenario PAST: Make the following decisions based on the COVID-19 climate 5 months ago, in March 2020. At this time, the total cases in the United States were 213 and the total deaths were 11. Now assume the choices you make could have effect on the life course of the pandemic to the present day.

Scenario PRESENT: Make the following decisions based on the current COVID-19 climate, in September 2020. The current confirmed cases in the United States is 6,189,488 and the total deaths are 187,541. Now assume the choices you make today could have an effect on the life course of the pandemic over the next 5 months.

Scenario FUTURE: Make the following decisions based on what the COVID-19 climate may be in 5 months, in February 2021. Now assume the choices you make could have an effect on the life course of the pandemic over the 5 months following this date.

The pandemic likelihood discounting questions were similar to the initial two experiments and took the form of:

Option A: Socially distance for X days, 0% chance of prolonged pandemic in U.S.

Option B: Socially distance for 0 days, $Y\%$ chance of prolonged pandemic in U.S.

Like in the other tasks, X was the number of days the participants would be willing to socially distance ranging from 15 to 60 days (i.e., 15, 20, 25, 30, 35, 40, 45, 50, 55, 60 days). The time was increased based on the incubation period of 2 weeks. Y was the titrations of the percent chance that a pandemic would occur (i.e., 0%, 10%, 20%, 35%, 50%).

Results and Discussion

Because the experimental manipulation of the third experiment focused on time (past, present, and future), the obtained data are shown in Fig. 5. Visual analysis of the data support the expected difference in discounting as a function of time, where greater mean pandemic likelihood discounting is observed in the past condition relative to the present condition. This is consistent with the temporal dynamics observed in Experiment 2 with a larger sample size and using the hypothetical timescale. It is interesting that there appears to be no discernable difference between the present and future conditions. This outcome is potentially important because if time is a variable that leads to lower pandemic likelihood discounting rates during a pandemic, then the discounting rates should be lowest in the future condition. One potential explanation is that participants can evaluate the state of the pandemic in the past because they experienced the past, but the future is necessarily uncertain and the future progression of the pandemic unknown.

The extra sum of squares F test was again conducted to compare the hyperbolic and hyperboloid models for these

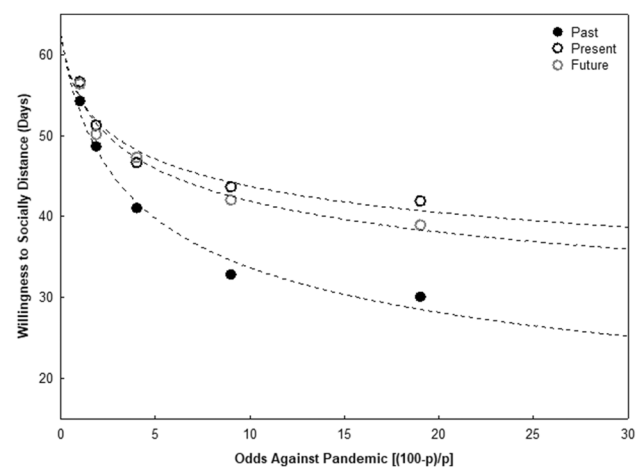


Fig. 5 Mean Indifference Point Data (Willingness to Socially Isolate) across the Three Experimental Conditions (Past = Circle; Present = Square; Future = Diamond). *Note.* Discounting curves were estimated using the hyperboloid curve function (Eq. 2)

data and in all instances the hyperboloid model was the preferred model (past: $F(1, 3) = 39.24, p < 0.01$; present: $F(1, 3) = 55.19, p < 0.01$; future: $F(1, 3) = 69.02, p < 0.01$). These models produced R^2 values of 0.98 in the past condition, 0.94 in the present condition, and 0.97 in the future condition, all exceeding the acceptability threshold. For the past condition, $h = 0.78, s = 0.28$; for the present condition, $h = 2.16, s = 0.11$; and for the future condition, $h = 1.49, s = 0.14$. Therefore, steeper discounting appears to be driven by the s parameter in the model when comparing across conditions. The best-fit hyperboloid models are shown in the figure.

AUC values are shown in Fig. 6 across the past, present, and future experimental conditions. The past condition produced a mean AUC of 0.576 (range: 0.24–1.0; $SD = 0.21$), the present condition produced a mean AUC of 0.67 (range: 0.29–1.0; $SD = 0.23$), and the future condition produced a mean AUC of 0.64 (range: 0.30–1.0; $SD = 0.30$). In addition to supporting the general conclusions from the data observed in the two-dimensional plot, the variability observed across each of the three conditions was high similar to the other two experiments. The Shapiro-Wilk test for normality suggested that only the past condition was normally distributed ($p = 0.79$), whereas the present and future conditions were not normally distributed ($p < 0.01$ and $p < 0.01$, respectively). Because the data were not normally distributed, a nonparametric Friedman ANOVA was conducted. The results of the Friedman ANOVA produced a value of 7.12, suggesting that AUC values in the past condition were significantly lower than in the other two conditions ($N = 34, df = 2, p = 0.03$). Dunn's multiple comparisons test of each of the three comparisons (Past vs. Present, Past vs. Future, Present vs.

Future) was conducted, where only the Past versus Future condition was statistically significant, adjusted $p = 0.04$.

Because the greatest difference was observed between the past and present conditions, within-subject effect size analysis was conducted that produced a moderate effect size of $d = 0.41$ and a post-hoc power analysis suggested that future studies comparing discounting rates across temporal experimental manipulations should recruit approximately 84 participants to avoid a Type 2 statistical error. In this experiment and in the previous experiments, the power analyses should be used simply to inform future research given the exploratory nature of the present study.

General Discussion

The results of this initial evaluation of choices related to social distancing and self-isolating during COVID-19 appear to suggest that these choices may be affected by contextual variables that are both naturally occurring and contrived. First, throughout each of the studies, a hyperbolic relationship was observed between one's perception of the risk of a pandemic occurring and their willingness to isolate or distance from others for a period of time. How behavior scientists communicate about public health crises to the general public can influence their decisions. Efforts to downplay the pandemic can undermine the perceived probability of risk of the pandemic (Kreps & Kriner, 2020), reducing the probability that the public engage in preventative public-health-related behavior. This general finding held true across multiple time periods (e.g., Experiment 1 and Experiment 2) and different groups of participants (e.g., Experiment 3).

Second, assurance that others will make similar choices to isolate appears to have an effect across time as demonstrated in Experiments 1 and 2. In both experiments, participants were more willing to self-isolate when there was assurance that other members of the community would make the same decisions. Consider that if one person chooses to self-isolate, the impact on the spread of the virus is negligible, and there is no assurance that this sacrifice now will actually reduce the probability that the spread meets pandemic levels. On the other hand, if all people agree to some level of distancing or self-isolating, epidemiological models suggest this can be effective to slow the spread (Te Vrugt et al., 2020; Teslya et al., 2020). Unfortunately, as demonstrated in an initial demonstration by Adaryukov et al. (2022) in the context of mask-wearing as a preventative measure, participants consistently estimated that compliance with prevention measures occurred less frequently for others than for themselves. Therefore, perception of the engagement of others with preventative policies like distancing or masking may be lower than the true rate that could lead to steeper discounting rates.

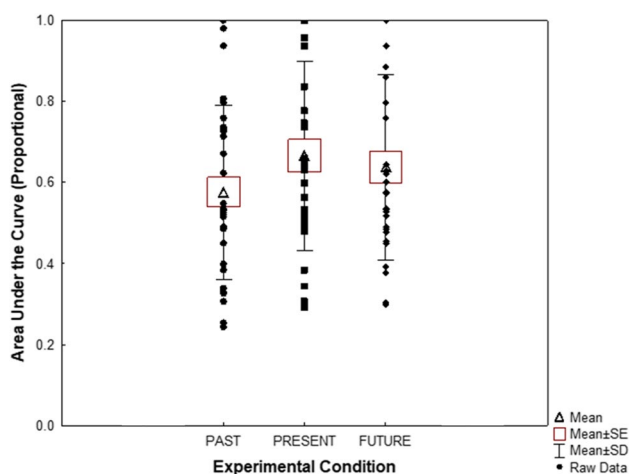


Fig. 6 Jittered Box and Whisker Plot of AUC Values across Past, Present, and Future Conditions. Note. Raw data points for each participant are displayed in the plot. Mean values are represented by triangles and standard error (box) and standard deviation (whisker) are shown in the plot

Third, results from all three experiments suggest that pandemic likelihood discounting rates may be steeper at the onset of a pandemic than later in the life course of the pandemic. This is true when comparing the discounting rates between Experiments 1 and 2, as well as in comparing results on the hypothetical timescale in Experiment 3. These data, if true, are potentially alarming because the moment in time when public-health decisions are made (i.e., at the onset of the public health crisis), is precisely the moment when pandemic likelihood discounting of public-health outcomes is likely to be the highest. It is up to policy makers to potentially “seize the moment” when public support of preventative measures is high. This interpretation is similar to basic experimental research on punishment, where the impact of the punisher is most salient after the event and dissipates over time. Experiencing COVID-19 may serve punishment functions, but if it does so, those functions are unlikely to last as new crises emerge between now and the next public health disaster.

Finally, the results from Experiment 3 suggest that similar patterns in decision making when all components of the pandemic likelihood discounting task are hypothetical, including the hypothetical timescale, may be apparent. A major limitation in this study is that a convenience sample was recruited to capture these data in the moment of the public health crisis. Behavior scientists have a lot of work to do before the next public health crisis, and these results suggest that providing hypothetical scenarios within pandemic likelihood discounting tasks can identify general trends or relationships that could inform public health policy.

As noted in Experiments 1 and 2, these results should be interpreted with caution due to the exploratory nature of the present set of experimental analyses. There are several limitations in the current research study; therefore, this study should be best viewed as preliminary within a larger research line. The sample in this study represented a convenience sample that was accessed by the research team based on available samples at the onset of the pandemic. The participation of this sample allowed for an analysis of contextual factors that might affect discounting during a pandemic; however, certainty that the same results would generalize to other samples is limited. In this case, the sample consistent of undergraduate college students who as population may skew more liberal than conservative (Honeycutt & Freberg, 2017; Peterson et al., 2020), where rule-governed behavior consistent within political ideology could be one factor that influences decision making. The current sample was also predominantly female and white; therefore, inferences that the same choices would apply within a more diverse sample are also limited.

Another limitation is that between Experiments 1 and 2, more than just the passage of time occurred. For example, masking mandates had been adopted across many states

and within many cities, COVID-19 cases and deaths had increased substantially, and more information was generally available during Experiment 2. The results suggest that time may be a feature worth exploring in future research as another contextual variable that could influence probability discounting during pandemic events. All of these factors are contained in the passage of time and the current research design cannot separate these variables. Another limitation related to the timing of the study is that self-isolating and social distancing are different terms that refer to different things. At the onset of the pandemic, isolating from others was initially recommended by the CDC, but this shifted to a social distancing strategy as more was learned about how COVID-19 spread. In retrospect, using the term “social distancing” in the initial experiments could have yielded different results. A third limitation is that the scenarios were presented in the framework of self-isolating, consistent with CDC guidelines at the time of this initial administration (CDC, 2020). Later in the progression of COVID-19, social distancing guidelines were released to slow the spread of the virus without the need to completely isolate from others (CDC, 2020).

Because the data were also collected in a hypothetical concurrent choice task, the degree to which reported choices would correspond with actual choices that people make requires further exploration. A further limitation of the choice task is the absence of a within-experiment comprehension check. Meaning that following the hypothetical scenarios, they were not provided with any clarifying questions to ensure competency or attentiveness to the scenarios that were provided. The above limitations are common in research on delay and probability discounting. Future research should also include a more diverse and larger sample size within probability discounting research, because this would account for an average as well as contribute to more impactful research within this focus area.

A next logical step in this research is to evaluate contextual factors that influence vaccine hesitancy as a form of probability discounting. Vaccinating can be seen as form of choice that involves competing probabilistic negative outcomes. On the one hand, not getting vaccinated confers a chance of contracting COVID-19 and a smaller chance of dying from it. On the other hand, getting the vaccine may reduce the chance of contracting COVID-19, but with a higher probability of feeling ill and a chance that “the experts are wrong” and terrible events may transpire. It is important to note that the probability of any long-term effects of the vaccine are minimal, but perception and reality are rarely aligned, opening up potential research avenues on the role of verbal behavior or rules on vaccine hesitancy and probability discounting. Are people more likely to get the vaccine if others are doing it? Is there a shift in vaccine discounting over time? A science of human behavior

could be immensely useful as behavior scientists navigate this or similar events in the future. A similar analysis could be applied to risks associated with mask-wearing in public spaces where temporary discomfort could delay or avoid illness later. As noted by Byrne et al. (2021), there appears to be a relationship between both risky decision making, temporal discounting, and mask-wearing in a U.S. sample. This analysis was extended by Strickland et al. (2022) in a large sample of 1,366 participants showing that choice architecture manipulations, such as opt-in/opt-out policies can promote or discourage behaviors like social distancing, mask-wearing, testing, and vaccination. As noted in Experiments 1 and 2, these results should be interpreted with caution due to the exploratory nature of the present set of experimental analyses. As more studies become available in behavior analytic journals, behavior scientists are developing an information ecosystem to inform public policy.

In summary, COVID-19 affected the lives of people throughout the world. Whereas epidemiologists were effective in predicting the progression of the pandemic and providing expert recommendations, efforts to change the choices people made were largely ineffective. The results of this current study suggest that two main contextual factors may predict whether people choose to isolate or distance. First, if people perceive the probability of a virus reaching pandemic levels is high, they may be more likely to follow CDC recommendations. Second, if the choice is left to each individual, people may be less likely to follow the recommendations. These results also provide some evidence that discounting may be steeper at the onset of a pandemic than later in the pandemic and that capturing similar patterns in using hypothetical manipulations based on time could inform future research related to behavior and public health.

Data Availability All data will be made available by emailing the corresponding author at the email address provided.

Declarations

Conflicts of Interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards

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