Behavioral Economic Modeling of the Effects of Symptom, Severity, and Cost on Seeking Medical Care

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BEHAVIORAL ECONOMIC MODELING OF THE EFFECTS OF SYMPTOM, SEVERITY, AND COST ON SEEKING MEDICAL CARE

by

Mark J. Rzeszutek

A dissertation submitted to the Graduate College
in partial fulfillment of the requirements
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While the United States has some of the highest healthcare spending in the world, it has some of the worst health outcomes. For example, maternal mortality in the United States is almost five times as high as in other similarly wealthy countries. It also has the highest rates of avoidable deaths. One of the reasons for this may be the cost of accessing healthcare due to privatized insurance. For example, Americans may avoid important preventive medical visits and other health screeners due to cost. While lack of health insurance has been correlated with decreased health utilization, a precise understanding of the determinants of care seeking has not been established. Modeling healthcare use based on common symptoms (e.g., cough, headache, nausea) can provide insight on how Americans may seek care for symptoms that could be indicative of more serious health problems. Modeling of decision-making can be accomplished through methods used in behavioral economics, most notably methods for studying intertemporal choice. Therefore, the purpose of present study was to apply behavioral economic methodologies to better understand healthcare utilization based on symptom, severity, and cost. Three experimental surveys each consisting of 200 participants recruited from Amazon Mechanical Turk were conducted. The first experimental survey consisted of monetary discounting of delayed or probabilistic rewards and losses as well as medical decision-making for seeking a medical professional based on symptom (i.e., cough, headache, nausea) and severity (i.e., mild, moderate, severe). With regard to monetary discounting, data replicated typical monetary discounting research. The gain/loss changes in discounting occurred for delayed and probabilistic
outcomes. With regard to health decision-making, as severity of symptom and duration of symptom experienced increased, so did likelihood to seek a healthcare professional. When cost was added as a factor in Experiments 2 and 3, increased costs decreased likelihood to seek a healthcare professional. Generally, models used in monetary discounting fit participant data well. When possible to assess the relationship between impulsivity, riskiness, and health decision-making, there was a positive relationship between seeking medical help and impulsivity. That is, those that were “more impulsive” based on monetary discounting were more likely to seek a healthcare professional for symptoms sooner. There was no relationship between impulsivity and riskiness as determined by monetary discounting, nor was riskiness related to health decision-making. For demographic variables, better health decreased the likelihood of seeing health professional, as well as for those who reported previously avoiding or delaying going to a doctor due to cost. The implications of these results are straightforward, in that associating a cost with healthcare will decrease the likelihood an individual will seek medical treatment at all levels of symptom severity. This study adds to growing body of data that the American medical system is in need of substantial reform if the goal is to keep all Americans healthy, rather than only those Americans who can afford it.
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In a more abstract sense, I’d also like to thank Tommy Douglas for helping to socialize healthcare in Canada which has led me to believe that healthcare is a right and not a privilege. On the flip side, I would like to thank the American healthcare system for being as broken as it is, for without all its flaws I would have needed to pick a less obvious dissertation topic.

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It’s the Prices, Stupid

The United States healthcare system is a paradox. Though the United States spends twice as much of its GDP on healthcare compared to other countries, it has the lowest average life expectancy, and some of the lowest birth weights (Papanicolas et al., 2018). For those who can access it, the United States has good preventive care compared to economically similar countries, but it also has the highest rates of avoidable deaths (Tikkanen & Abrams, 2020). When compared to Canada, a relatively similar country with socialized rather than privatized health insurance, the impact of socioeconomic status (SES) on health was higher in the US than in Canada (Wilson, 2009). And while cancer deaths are on the decline in United States (CDC, 2020a), disparities exist in the form of increased cancer deaths for those who are either low SES or non-white (Ward et al., 2004). Similarly, the maternal death rate for African-American women is four times higher than that of white women, and the infant mortality rate is nearly three times as high (Taylor, 2019). In fact, the United States has an abnormally high maternal death rate when compared to similar countries (Sawyer & McDermott, 2019).

Part of the differences between health outcomes, especially for preventable deaths may have a simple explanation which is stated succinctly in the titles of papers by Anderson et al. (2003), “It’s the prices, stupid” and Anderson et al. (2019) “It’s still the prices, stupid”. The average cost of healthcare spent per person in the United States is twice that of comparable countries (Sawyer & McDermott, 2020). Most importantly, medical debt the is most common form of personal debt in the United States (Doty et al., 2008; Himmelstein et al, 2009; Himmelstein et al., 2019). This high cost of healthcare, and potential fear of medical debt, may deter Americans from utilizing preventive medical services that will decrease larger, worse outcomes later. Using cancer as an example, Etzioni et al. (2003) argue that early detection is an
important factor for cancer outcomes, but for cancer to be detected, and therefore treated, early, an individual first must get the appropriate health screener. However, if people are unable to afford or are deterred by cost of a screener, early detection is not possible. Ward et al. (2004) found that preventive screens were at times less than half as likely to occur for those without health insurance, and also found that stage of cancer (i.e., how much the cancer has spread), was higher for those in areas with higher poverty rates. Less advanced cancers would also be easier to treat, and therefore less costly to treat. If people cannot access healthcare, they cannot have a potentially deleterious health condition identified or treated.

Generally, healthcare utilization is negatively correlated with distance to clinics (Buzza et al., 2011; Virgilsen et al., 2019), cost of service (Kullgren et al., 2010), ethnic group (Bradley et al., 2001), socio-economic status (Kullgren et al., 2010), and being male (Boman & Walker, 2010). However, how any given individual will access healthcare is not clear. Currently, no quantitative analysis exists on how individuals might seek healthcare for commonly occurring symptoms, such as those that might occur during a flu or cold (e.g., cough, headache, nausea). For example, while a mild headache that lasts a day may not be indicative of an underlying condition, a headache that persists for weeks could be a symptom of cancer (American Cancer Society; ACS, 2020) or a variety of other causes (Mayo Clinic, 2020). Therefore, quantifying exactly how an individual decides to seek healthcare for common symptoms, with different costs to access healthcare, could greatly enhance understanding of when and how someone will make medical- and health-related decisions.

**Behavioral Economics**

One of the possible ways to assess health-related decision-making is through methods developed in the behavioral economic tradition. Contrasted to classical economics (i.e., rational
choice), behavioral economics assumes that many factors will affect decision-making (i.e., irrational choice; Angner, 2016). What it means to behave rationality as per classical economics is simply if an individual follows a normative model (i.e., how classical economists believe people ought to behave). Behavioral economics instead uses descriptive models (i.e., how people actually behave). One of the most popular examples of this so-called irrational decision-making is the Asian disease problem (Tversky & Kahneman, 1981). In the Asian disease problem, participants are presented with a choice between two possible treatments for a disease that will kill 600 people. The first two treatments are (a) 200 people will be saved or (b) there is a 1/3 probability that 600 people will be saved, and a 2/3 probability that no one will be saved. When presented this way, the majority of people pick option (a). However, when the treatments are presented as (c) 400 people will die or (d) there is a 1/3 probability that no one will die, and a 2/3 probability that 600 people will die, the majority of people will pick option (d). This is odd, as mathematically (a) and (c) are equivalent, as well as (b) and (d). A rational actor would be expected to make the same choice between both forms of questions, but people weigh outcomes differently based on the way they are presented.

Another example of irrational choice according to classical economics is seen in intertemporal choice, where one decides between two or more outcomes occurring at different times (see Frederick et al., 2002 for a comprehensive review). Samuelson (1937) provided a conceptual framework of utility (i.e., value) of a commodity being discounted in an exponential fashion. Basically, the more delayed an outcome is, the less value it has. That is, the value of an outcome is discounted as a function of time. Therefore, Samuelson proposed an initial model of delay-discounting with an exponential decay. This form of discounting from classical economics contains the assumption that general preferences between outcomes will remain stable as time
changes. That is, if one were to value $1,000 higher than $100 dollars, they would always value $1,000 as higher than $100, even though the subjective value of both has changed as a result of a delay. Instead, individuals will switch their preference (i.e., select the lesser valued option instead of the higher valued option) between outcomes as the time to the less valued reward decreases (e.g., Green et al., 1994). For example, an individual who decides to not buy chocolate before going grocery shopping but buys chocolate once at the grocery store. Another example would be someone deciding to go to the gym and exercise but on the way to the gym instead buys a bag of chips and avoids the gym. This time-inconsistent preference-switching is known as preference reversals.

Hyperbolic Discounting

Rather than discounting outcomes exponentially, humans instead discount values of delayed outcomes in a hyperbolic fashion (Rachlin et al., 1991; Vandervelt et al., 2016) in contrast to the original Samuelson (1937) formulation of discounted utility with exponential decay. Rather than an outcome being discounted constantly over time, its value instead sharply drops and then levels off. This is known as hyperbolic discounting (e.g., Madden & Johnson, 2010; Odum, 2011) and appears to account for preference reversals. An excellent example of preference reversal relevant to medical-decision making is found in Christensen-Szalinski (1984). In this study, pregnant women were asked how important it was to deliver their child without anesthesia, and how concerned they were about avoiding hard labor pains. Before labor, women generally preferred avoiding anesthesia. However, during labor, they overwhelmingly changed their preference to avoiding pain. After childbirth the mothers’ preferences returned to avoiding anesthesia. As the time\(^1\) to the outcome changed, in this case labor, preferences

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\(^1\) As well as other environmental factors like pain.
changed. More importantly, the exact time a preference reversal would occur can be identified through what are known as indifference points (explained below). Use of these indifference points and hyperbolic modelling also allow for predicting when an individual might engage in some health behavior. For example, Jarmolowicz et al. (2016) determined the specific point when individuals with multiple sclerosis would be likely to take a disease modifying treatment based on the treatment’s effectiveness and side effect severity. The strength of this approach allows for not only understanding how decision-making for health outcomes is affected by various factors, but it can also be used to predict the amount of that factor is needed for individuals to make a decision. Therefore, these models have the potential to be extended to predict and understand other medical and preventive behaviors, such as treatment seeking for specific symptoms experienced for varying durations.

The original method to determine indifference points for humans (i.e., the point at which a preference switches between two outcomes) was developed by Rachlin et al. (1991). For this method, a participant is asked to decide between two, typically monetary, options. One option is for an immediate amount, whereas the other is the same amount but delivered later. An individual’s subjective value between these two options is then derived by asking a series of questions where the value of immediate amount is systematically decreased while the delay remains fixed. When the individual switches preference from the larger, delayed reward to the smaller, immediate reward this is referred to as an indifference point. The indifference point can be interpreted as the subjective value of the larger later commodity at a given time point. For example, if a participant reverses preference from the immediate reward of $500 to a reward of $1,000 at a delay of one month, the subjective value of $1,000 at one month is equal to $500, or half of its original value. This procedure is then continued with various delays tested, and
indifference points are obtained for each delay. Indifference points are then used to calculate a discount rate, which is also considered an index of an individual’s impulsivity. This is because it is assumed that someone who chooses the smaller, sooner outcome is unable to wait to access the larger, and presumably better, delayed outcome. Higher discount rates result in steeper curves, and lower discount rates result in shallower curves. Because of this, high discount values and steeper curves will be used interchangeably to describe those that are considered more impulsive.²

Calculating Discounting

Prior to discussion of factors that affect discounting, and discounting specific to health-related decision-making, it is important to overview how discounting or discount rates are typically determined. To calculate discount rates, there are at least 26 different models that have been used or proposed (see Doyle, 2013). Due to their popularity, only four models will be described in detail: Exponential, hyperbolic, Green and Myerson hyperboloid, and Rachlin hyperboloid. Also, ways to calculate discounting will be presented as those with a priori assumptions of discounting (i.e., theoretical) and those without (i.e., atheoretical). Separation of these two categories is important, as theoretical assumptions that well describe monetary discounting may not be appropriate to use for health-related discounting (see Van der Pol & Cairns, 2011). There are many procedures used to assess discounting in humans, but all of them use derived indifference points from which the following calculations can be applied.

Theoretical Discounting Rate Calculations

Samuelson (1937) initially proposed an exponential model for decaying subjective value over time. This model follows the form \( V = Ae^{-kD} \), henceforth referred to as the exponential

² However, the exact nature of the impulsivity being measured via discounting has been debated (see Green & Myerson, 2013).
model, where \( V \) is the subjective value of a commodity, \( A \) is the undiscounted amount of that value, \( k \) is the discount rate, and \( D \) is the delay to the commodity.

Mazur (1987) proposed an alternative model to discounting future outcomes in the form of a hyperbolic function following the form \( V = A/(1 + kD) \), henceforth referred to as the hyperbolic model, where \( k \) represents the discounting rate. For this formula and those that follow, \( V \) and \( A \) represent the same variables as in the exponential model. This model has the advantage of being empirically derived, whereas the exponential model is conceptually derived. While the original hyperbolic model focuses on delay to an outcome or a reward, it can be generalized to other situations, such as the probability of an outcome or the social distance of someone receiving an outcome. For example, Rachlin et al. (1991) used the variation of \( V = A/(1 + h\Theta) \), for comparing discounting of probabilistic outcomes, where \( \Theta \) is the odds against an outcome and \( h \) is the discount rate. The calculation for odds against is \( \Theta = (1 - p)/p \), where \( p \) is the probability of an event. In the case of probability discounting, lower \( h \) values are thought to indicate an individual’s riskiness. This is because lower \( h \) values indicate more choices towards the probabilistic outcome rather than the certain outcome. Social discounting using the hyperbolic model is much the same as the previous delay and probability formulas (Jones & Rachlin, 2006), \( V = A/(1 + sN) \), where \( N \) is the social distance from someone (e.g., child, sibling, cousin, friend, stranger) and \( s \) is the discount rate. In the case of social discounting, an individual can choose between smaller option for themselves, or a larger option for the other person. For social discounting, higher \( s \) values are thought to be indicative of selfishness. This is because higher \( s \) values require individuals to have chosen some smaller amount of money for themselves over a larger amount for others.
Myerson and Green (1995) proposed an adjustment to the hyperbolic model, where the scaling parameter $s$ is added to the denominator, $V = A/(1 + kD)^s$. This equation will henceforth be referred to as the GM hyperboloid model. When $s$ is 1, this equation is identical to the hyperbolic model. The scaling parameter $s$ is meant to represent the typically nonlinear scaling of time or odds against (Green & Myerson, 2004). Rachlin (2006) also proposed an alteration to the hyperbolic model, where a psychophysical scaling parameter $s$ is added to delay, $V = A/(1 + kD^s)$. This model will be referred to as the Rachlin hyperboloid.

Yoon and Higgins (2008) proposed a relatively simple conversion from the $k$ value estimated from the hyperbolic model to be able to identify at what delay an individual is indifferent between outcomes across delays, the effective delay 50 (ED50). The calculation for this is simply ED50 = 1/$k$. Practically speaking, the ED50 is an easy way to convert and interpret $k$ values, as $k$ on its own is relatively uninformative without context. In the case of ED50, the specific point (e.g., day, probability, social distance) where an individual becomes more likely to pick the smaller sooner option over the larger later option. For other outcomes, like EP50 (Jarmolowicz et al., 2016), the point found by inverting the discounting parameter indicates when an individual might engage in a particular behavior based on the independent variables.

The hyperbolic and both hyperboloid models outperform the exponential model for fitting indifference points, with both hyperboloid models generally outperforming the hyperbolic model (Franck et al., 2015; Gilroy et al., 2017; McKerchar et al., 2009). Between the hyperboloid models, the GM and Rachlin versions appear to provide similar fits to the data, with the Rachlin hyperboloid slightly outperforming the GM hyperboloid. While these various discounting models have been successful in describing discounting in humans, all require theoretical assumptions. Not all humans will discount systematically (see Johnson & Bickel,
2008; Smith et al., 2018), which can result in poor fits for all models. Because of this, atheoretical approaches to calculating discounting have been proposed.

**Atheoretical Discounting Rate Calculations**

Myerson et al. (2001) described a procedure to calculate an overall measure of discounting called area under the curve (AUC). After normalizing the delay, probability, or social distance, and whatever value A was set to range from 0 to 1, AUC is calculated by adding all the polygons for each interval to create a value from 0 to 1. The formula for this is $AUC = \sum_{i=1}^{n}(x_2 - x_1)[(y_1 + y_2)/2]$, where $x_1$ is the smaller value of the normalized interval, $x_2$ is the larger value of the normalized interval, and $y_1$ and $y_2$ are the normalized indifference points at $x_1$ and $x_2$ respectively. All polygon areas are then summed together to generate a single AUC value for an individual. Higher AUC values indicate shallower discounting, whereas lower AUC values indicate steeper discounting. An AUC of 1 means that only the larger delayed outcome was selected across all delays, while an AUC of 0 indicates only the smaller sooner outcome was selected across all delays. While this approach has benefits, it has two major issues. It cannot be used to predict the subjective value at a time point not tested, and it is insensitive to the direction of discounting. For example, someone who displayed perfect linear discounting (i.e., a diagonal line) who chose 100% the larger option at no delay, 50% of the larger option at the middle delay and chose the larger option 0% at the last tested delay would have an AUC value of 0.5. By contrast, someone who had consistent indifference across time points (e.g., 50% at all delays) would also have an AUC of 0.5. If someone had a perfect linear increasing discount curve (i.e., 0% larger option at no delay, 50% larger option at the middle delay, and 100% larger option at last tested delay) would also have an AUC of 0.5. Because of this, for AUC to be a fair assessment of discounting, it is necessary to consider the way an individual has answered
discounting questions. AUC calculated in this way also does not take into considerations of delay or probability scaling like the theoretical models.

To improve upon the AUC calculations introduced by Myerson et al. (2001), Borges et al. (2016) proposed two alternative methods to implement prior to normalizing the data. The first is by log scaling the delay before normalizing the data, then calculating AUC as described above. This results in $AUC_{\text{log}}$. For cases where the lowest delay is 0, a small constant can be added to prevent issues with log transforming 0 (i.e., log transforming 0 results in negative infinity). The second way is by rank ordering the delays, thereby resulting in equal weighting for all intervals, and calculating AUC as described above. This then becomes $AUC_{\text{ord}}$. Borges et al. found that $AUC_{\text{log}}$ and $AUC_{\text{ord}}$ were both able to detect the magnitude effect in previous datasets where AUC could not, providing an empirical basis for the superiority of $AUC_{\text{log}}$ and $AUC_{\text{ord}}$ over AUC.

Factors that Affect Discount Rates

Once discount rates are calculated for individuals, regardless of method of calculation, comparisons can be made on how people discount specific commodities using the derived discount rates. There are several ways that hypothetical situations are presented that will consistently affect discounting. Some effects relevant to health-discounting will be briefly discussed.

Magnitude of the Outcome

A robust effect that has been found is that the size of the outcome will affect how individuals discount. For example, while the proportional difference between $5 and $10 is the same as $500 and $1,000, people will have significantly different discount rates between the two commodities. When discounting a delayed commodity, people will discount smaller values more
than larger values (e.g., Baker et al., 2003; Blackburn & El-Deredy, 2013; Chapman, 1996; Weatherly & Terrell, 2014). They act more impulsively towards smaller values than larger values. However, the opposite effect is found for discounting a probabilistic outcome (e.g., Du et al., 2002; Myerson et al., 2011; Weatherly & Terrell, 2014; Yi et al., 2006) where larger values are discounted more than smaller values. In the case of probability discounting, increased magnitude decreases riskiness.

**Sign of the Outcome**

Another robust effect that has been found to impact discount rates is whether an individual is choosing between gains or losses. For example, people will discount gains of $50 now or $100 later more than they will discount losses of $50 now or $100 later (e.g., Baker et al., 2003; Furrebøe, 2020; MerKerchar et al., 2013; Rzeszutek et al., under review). More specifically, people will choose a delayed loss more often than a delayed gain when the absolute difference between the alternatives are the same.

**Magnitude and Sign of the Outcome**

Interestingly, the magnitude is moderated by the sign of the commodity. The magnitude effect does not appear to occur for losses of delayed or probabilistic outcomes (Green et al, 2014; MerKerchar et al., 2013). That is, the discounting of losses is not affected by how small or how large, the loss is. Losses appear to be discounted consistently.

**Type of Outcome**

The last factor that will be discussed that affects discounting is the nature of the commodity of the outcome being discounted. Odum et al. (2020) conducted a systematic review of studies that measured delay discounting of monetary outcomes and at least one non-monetary outcome. The overall finding by Odum et al. was that non-monetary outcomes are more steeply
discounted than monetary outcomes. In some cases, discounting rates between monetary and other outcomes (e.g., food, cigarettes, drugs) were correlated, but this correlation between health discounting and monetary discounting was inconsistent.

**Discounting and Health-Related Behaviors**

There are several major areas where steeper delay discounting (i.e., higher impulsivity) of monetary rewards has been correlated with unhealthy behaviors (e.g., smoking, excessive eating, risky sexual behavior). In a systematic review by Story et al. (2014), the authors found that higher monetary discount rates would predict smoking, alcohol use, other drug use, and an emerging relationship with obesity. Story et al. also found that there was mixed but emerging evidence of lower rates of discounting being associated with preventive health behaviors (e.g., mammograms, prostate exams, flu shot, dental visits). In two meta-analyses by MacKillop et al. (2011) and Amlung, Vedelago, et al. (2016) an association between addictive behaviors (i.e., alcohol, tobacco, gambling, cannabis, and stimulant use) and delay discounting was found. A meta-analysis of the discounting of food and monetary rewards by Amlung, Petker, et al. (2016) found that those who were considered obese discounted more steeply than those who were not. Monetary discounting is also related to psychiatric diagnosis. Amlung et al. (2019) conducted a meta-analysis of monetary discounting and various mental health diagnoses. They found that for major depressive disorder, schizophrenia, borderline personality disorder, bipolar disorder, obsessive compulsive disorder, bulimia nervosa, and binge eating those with a diagnosis were more likely to discount delayed monetary rewards. Only in the case of anorexia nervosa was there a decrease in discounting. This makes intuitive sense, as anorexia nervosa is the virtual opposite of binge eating.
Because of the generally robust relationship between steep discounting and unhealthy behaviors, this has lead conceptualizing excessive discounting as part of a trans-disease process (e.g., Bickel et al., 2019; Bickel et al., 2012; Bickel & Mueller, 2009). The idea of a trans-disease process is relatively straightforward. Excessive discounting of reinforcers (e.g., food, money, drugs) is in part due a common underlying mechanism. Bickel et al. (2012) argue that this excessive may be due in part to competing neurobehavioral systems, where parts of the brain activated for choices for immediate reward (e.g., limbic system) are in competition with the parts of the brain that are activated during choices of delayed reward (e.g., prefrontal cortex). Excessive discounting of reinforcers occurs when the limbic system is more activated during valuations of reward than the prefrontal cortex (Bickel et al., 2011). This may be part of the reason why there excessive discounting is so correlated with unhealthy behaviors that are typically defined by excess (e.g., overeating, drug use, risky sex). The review by Amlung et al. (2019) on discounting and psychiatric disorders provides some diagnostic evidence of this idea, as many psychiatric issues share a trans-diagnostic process involving cognitive control (McTeague et al., 2016). However, whether this trans-disease model of excessive discounting applies specifically to medical discounting and decision-making is not yet clear.

**Health and Medical Discounting**

The following section is divided into two categories, studies that directly compare health outcomes with monetary discounting or other commodities, and studies that explicitly explore how people make health-related decisions. In the former category, these studies combine traditional monetary discounting and various health-related scenarios. These health scenarios will sometimes involve a hypothetical medical treatment, or some general preference in health outcomes based on various delays or probabilities. In the latter category, the majority of these
studies are typically focused on choosing between hypothetical medications or treatments that vary in effectiveness, side effect severity, or delay to improvement or deterioration of health conditions. Studies are ordered by research group and chronologically for each category. Due to their relevance to the proposed study, each study that focuses on health or medical discounting will be discussed in detail.

*Health and Medical Decision-Making Compared to Other Commodities*

Chapman & Elstein (1995) compared discount rates of between money, vacations, and long-term health over two experiments. In the first experiment, discount rates were derived for hypothetical lottery, vacation, and health scenarios for 70 undergraduate students. For all scenarios across commodities, delays assessed were at 6 months and 1, 2, and 4 years. Questions were fill-in-the-blank (FITB) format, where participants were asked to write the value of the delayed prospect that would be equivalent to the immediate prospect. For example, participants could either receive a hypothetical $200 now, or some value of their choosing two years from now. For monetary questions, immediate values of $200, $1,000, $5,000, and $25,000 were used. Vacation questions were presented as choosing between an immediate trip for some time, or a participant chosen value after a delay. For vacations, the immediate value was two three, seven, or 14-nights, and the location was varied between Galena, Florida, Bermuda, and Europe. Health questions were presented as the participant were experiencing hypothetical symptoms and could choose between an immediate treatment that would last some time, or a value of improved health after a delay. For health, immediate values of improved health were six months, and one, two, or four years. Discount rates were calculated using the formula \( r = \left( \frac{V_d}{V_0} \right)^{1/d} - 1 \), where \( V_d \) is the reported value of the delayed option, \( V_0 \) is the magnitude of the immediate option, and \( d \) is the delay. A 4x3x3 ANOVA using log discount rates found significant main effects for delay,
magnitude, and domain. Significant interactions were all identified. A factor analysis identified that domains were relatively independent between each other, that is steep monetary discounters were not also steep health discounters. Experiment 2 was a replication of Experiment 1, with only health and monetary questions conducted with 34 undergraduate students. Delays used were one, three, six, and 12 years. Monetary magnitudes were adjusted to $500, $1,000, $2,000, and $4,000, whereas health magnitudes were adjusted to one, two, four, and eight years. Much like in the first experiment, health and monetary discounting were weakly correlated. Also, health discounting rates were higher than monetary discount rates. In both experiments, higher magnitude rewards were discounted less than smaller magnitude rewards.

In a series of three experiments Chapman (1996) compared health and monetary discounting and their domain independence. The first experiment was identical to the second experiment of Chapman and Elstein (1995). Discounting rates were also calculated the same way as Chapman and Elstein (1995). Eight exchange rate questions were added, where participants reported the worth in money or time in full health for each magnitude would be equivalent to the alternative commodity. Forty undergrads were the participants of the first experiment. Results were similar, in that discounting rates were higher for health outcomes than monetary outcomes, but that the two domains appeared to be independent and weakly correlated. For exchange rates, money was always weighted higher than health. Discount rates were not related to exchange rates. Experiment 2 consisted assessing framing and the sign effect on monetary and health outcomes. Monetary magnitudes were $500, $1,500, and $4,500, whereas health magnitudes were .5, 1, and 1.5 years. The delays used were one and nine years. Magnitudes for money and health were matched using the exchange procedure from the first experiment. There were 77 participants in the second experiment. Losses were less discounted than gains for money and
health, and health was discounted more steeply than money. Domains were not correlated with each other. The third experiment consisted of 38 undergrads who completed questions used to derive utility functions. They would answer questions where they would fill in a value that would subjectively equal the feeling of receiving $500 when they expected $0, but with the interval ranging from $500 to their chosen value. The next interval tested would be $500 to their identified value, for a total of four times. The function to determine utility was $U = a(Q^b)$ where $Q$ is quantity of health/money, and $a$ and $b$ were parameters specific to the participant, domain, and sign. Utility functions were for money followed the traditional s-curve as in Tverksy and Kahneman (1981), while utility functions for health were nearly straight diagonal lines.

Chapman et al. (2001) conducted a series of three experiments that compared hypothetical monetary and health questions to real-world health behaviors. In the first experiment, university faculty and staff were recruited via mailed questionnaires. These questionnaires contained questions about flu-shot acceptance, monetary time preference, and health time preference. Monetary time preference was assessed by a series of four questions concerning paying a hypothetical fine now for a fixed price or a varied fine for fixed price after four months. Health time preference was assessed in a similar way but for experiencing a flu now for seven days or for a varied number of days after four months. Participants were also mailed follow-up questionnaires at six months and a year to assess flu shot adherence and test-retest reliability. Some participants were also asked if they invested in a retirement fund. The results of the first experiment were indicative of no relationship between health time preferences for either flu shot acceptance or retirement investments. Monetary time preference was significantly but weakly correlated with flu shot acceptance. The second experiment consisted of hypothetical hypertension scenarios for 195 older adults that were living in communities and
being treated for hypertension. The health scenario involved a hypertension drug that decreased some chest pain now, or another drug that decreased more chest pain later. Monetary scenarios were phrased in a similar way but with an immediate tax rebate against a larger, delayed tax rebate. Indifference points were determined by a titrating procedure. Adherence measures were also taken in the form of self-report, pill count, and blood pressure. Monetary time preference was not related to medication adherence, although health time preferences were sometimes weakly correlated with measures of adherence. The third experiment consisted of questions about cholesterol to 169 patients currently being prescribed a cholesterol medication. The hypertension from the previous experiment was used but changed so the hypothetical situation involved them suffering from some heart condition that caused chest pain. Medication adherence was determined by self-report and cholesterol levels. There was no significant correlation between health time preference and medication adherence.

Baker et al. (2003) compared cigarette smokers and never smokers on discounting of money, health, and cigarettes. Participants completed three sessions. The first session consisted of standardized tests, and hypothetical health-value questions. Smokers also completed hypothetical cigarette-value questions. Questions consisted of hypothetical scenarios of where a participant identified what the equivalent duration a 10% improvement or decrement in health was to be as attractive as $1,000. Cigarette equivalence was the same health, but with the number of cigarettes being as attractive as $1,000 right now. The second session consisted of monetary, health, and cigarette (for smokers) discounting questions. Participants would respond to questions similar to the first session, but with varying delays associated using a titrating procedure with adjusting limits to identify an indifference point. During these discounting questions, gains and losses were tested, and three values of money ($10, $100, $1,000) were
assessed. For smokers, cigarette discounting was compared at the same three values of money. Health discounting was only comparing an improvement/decrement in health being as attractive as $1,000. In the second session, participants also were able to choose between a real monetary amount now or at a delay. Participants were randomly assigned to either a real monetary value of $10 or $100. The third session was identical to the second session. There were 60 total participants, with equal numbers of smokers and never smokers. Values of \( k \) were estimated using the hyperbolic model. Smokers had higher \( k \) values on average when compared to never smokers on all outcomes. For money, a 2x2x3 repeated measures ANOVA identified significant main effects of smoking, magnitude, and sign, with significant interactions for smoking and magnitude and sign and magnitude. For health, a 2x2 repeated measures ANOVA identified a significant main effect on sign, but not smoking. For real monetary outcomes, a 2x2x2 repeated measures ANOVA identified main effects of smoking status and magnitude, with a significant interaction between hypothetical/real and magnitude. Discount rates were higher for money than health in smokers and never smokers.

Weatherly et al. (2010) compared 10 different commodities in a sample of 791 undergraduates. Using a FITB procedure, participants could indicate the monetary value of a later option that would be equivalent to an immediate option of a commodity. Participants could have either been given one of two sets of questions. The first set of questions consisted of winning $1,000, winning $100,000, their ideal body image, their ideal romantic partner, and cigarettes. The second set consisted of being owed $1,000, being owed $100,000, annual retirement income, medical treatment, and federal legislation on education. In the case of the medical treatment, the hypothetical situation was that a medication for a serious disease which was 100% effective but only after some delay, participants would then indicate what was the
minimum acceptable effectiveness for a medication available immediately. AUC was calculated to determine discounting. Participants discounted being owed $1,000 more than any other commodity. Medical treatment was discounted more than retirement income and federal legislation. A factor analysis indicated that medical treatment was in a different factor from being owed money or retirement.

Weatherly and Terrell (2011) conducted a direct replication of Weatherly et al. (2010) with 236 undergraduates. AUC was calculated to determine discounting. Results of Weatherly and Terrell (2011) were the same as Weatherly et al. (2010).

Weatherly et al. (2011) replicated and extended Weatherly et al. (2010) by assessing the test-retest reliability of the FITB method with 115 undergraduates. Questions and sets were identical to the previous Weatherly and colleague studies. Participants first completed either set A or B, and then completed it again 12 weeks later. Both AUC and hyperbolic model were used calculate discount rates to compare test-retest reliability. Estimates of $k$ were log transformed before statistical tests were conducted. In the case of all commodities, bivariate correlation was generally high (-.617 to -.982) for log $k$ and AUC at both time points. Generally, log $k$ was found to be more different from first to second tests than compared to AUC. When using AUC, medical treatment discounting was not correlated between first and second tests ($r = .019$), while log $k$ for medical treatment was correlated ($r = .639$).

Weatherly and Derenne (2013) compared the test-retest reliability of two methods of producing indifference points, the FITB method and a multiple-choice method. The multiple-choice method involved participants choosing on of 51 possible choices of their equivalent probability or dollar value of a larger commodity which was relative to that certain commodity. Participants were 233 undergraduate students who completed FITB or multiple choice (MC)
versions of a probability task at zero, four, and 12 weeks. The hypothetical medical treatment question involved a participant choosing the minimum percent of improvement produced by a medical treatment relative to one that completely cures the disease for a certain percentage of people who take it. Probability discounting rates calculated using the hyperbolic and GM hyperboloid models, along with AUC. Medical treatment was generally less discounted than other commodities on all metrics, while FITB generally appeared to be more reliable across time than MC. Curves fit using the GM hyperboloid were considered the better model as determined by AIC values than the hyperbolic for nearly all commodities and methods.

Weatherly and Derenne (2014) compared online and in-person data collection of probability discounting as an extension and replication of Weatherly and Derenne (2013). Participants were 650 undergraduates who completed either an in-person FITB or MC probability discounting task, or an online FITB or MC discounting task. Questions used were the same as Weatherly and Derenne (2013). Weatherly and Derenne (2014) found that there were differences between group responses from in-person and online questions, and that MC questions produced shallower discounting than FITB questions. Medical treatments were generally discounted less than other commodities much like in previous probability discounting research.

Weatherly and Terrell (2014) studied differences in the magnitude effect for delay and probability discounting of monetary and medical outcomes. Hypothetical questions were FITB, where participants would indicate the minimum acceptable amount of money or success of treatment now as opposed to a delayed larger outcome. This same question format was used for probability discounting, with delay replaced by the probability of receiving the larger outcome. For money, $100 and $100,000 were the small and large magnitudes respectively. For medical treatments, acne treatment and brain cancer treatment were the small and large outcomes.
respectively. For the delay scenarios, 166 undergraduates completed the questionnaires. For probability scenarios, 181 undergraduates completed the questionnaires. AUC was used to calculated discounting. For delay, smaller magnitudes were discounted more than larger magnitudes for monetary and medical outcomes. For probability discounting, the magnitude effect occurred for both outcomes. However, the magnitude effect was inverted for monetary outcomes (larger values were more steeply discounted) whereas this did not occur for medical outcomes.

Sawicki and Markiewicz (2016) replicated and extended Weatherly and Terrell (2014) by studying magnitude of monetary and medical treatments where medical outcomes were either discrete or divisible. Procedures were identical to Weatherly and Terrell (2014), but some questions compared body paralysis instead of brain cancer, and a visual analogue scale (VAS) was used instead of FITB. The authors assessed delay and probability discounting. Participants were also asked of their hypothetical worry for low- and high-intensity acne, brain cancer, and body paralysis. AUC was used as the measure of discounting. Results of Weatherly and Terrell (2014) were replicated by Sawicki and Markiewicz (2016) for discrete outcomes, but the divisible outcome (body paralysis) behaved more similarly to monetary outcomes. However, for probability the magnitude effect was not observed with divisible health outcomes. Participant’s worry between high- and low-intensity outcomes was lower for brain cancer than acne and body paralysis.

Friedel et al. (2016) replicated and extended Baker et al. (2003) by comparing discounting of money and two different health commodities between smokers and nonsmokers. Using an adjusting amount procedure, Friedel et al. (2016) used hypothetical questions similar to Baker et al. (2003), with the exception of the larger monetary value being $500 rather than
$1,000. Questions consisted of monetary gains, monetary losses, health gains much like Baker et al. (2003), and a curative medical treatment based on the questions used in Odum et al. (2002). These medical questions consisted of a hypothetical situation where participants were experiencing AID-like symptoms following sex with a stranger. In this hypothetical medical scenario, participants could choose between a medication that provided an immediate relief in symptoms, or a delayed improvement in symptoms Participants were 38 smokers and 32 nonsmokers. Values of $k$ were estimated using the hyperbolic and Rachlin hyperboloid models. ED50 was also calculated for all participants and questions. Smokers overall had steeper discounting for monetary gain, the health boost, and the health cure. Discounting was generally correlated between health boost, health cures, and monetary gains. The hyperbolic model better described nonsmoker’s discounting, whereas the Rachlin hyperboloid better described smoker’s discounting.

**Medical Decision-Making**

Odum et al. (2002) compared discounting of health outcomes in current, ex-, and never-smokers. There were two scenarios assessed. The first health scenario presented participants a situation, where following sex with an attractive stranger, they started experiencing health issues (AIDs-like symptoms) and loss of friends as a result of it. Participants would then indicate whether they would prefer a treatment that immediately improves their health for some duration, or an outcome that improves their health for 10 years after a delay. There were 27 durations of improvement ranging from 10 years to 0.01 years. Seven values from 3.6 days to 10 years were assessed in an ascending/descending procedure. The second health scenario was similar to the first, but instead of choosing between a treatment, participants would choose between immediately experiencing 10 years or symptoms, or 10 years of symptoms following the same
delays used in the first scenario. Participants were 23 current smokers, 22 never smokers, and 21 ex-smokers. Values of $k$ were derived from the exponential and hyperbolic models. Generally, current smokers discount gains and losses more steeply than ex- and never-smokers. Ex-smokers discounted between current and never-smokers but were not statistically different from either group. Smokers and ex-smokers discounted health losses more than gains, but this did not occur for never-smokers. In all cases but individual data for health gains, the hyperbolic model provided better fits than the exponential model.

Bruce et al. (2015) using discounting methods to assess medication adherence by patients with multiple sclerosis (MS). Bruce et al. used the Medical Decision Making Questionnaire (MDMQ) which is a VAS where an individual can mark off how likely they are to engage in some health behavior (i.e., medication adherence) at some probability of side effect. For chronic diseases, adherence to disease-modifying treatment (DMT) is often problematic due to side effects that result from the DMT. Participants were divided into two categories, the 39 who were adherent to MS medication, and 38 were not adherent. Participant adherence was determined by their self-reports of the participants in a screening questionnaire. In this study, the MDMQ consisted of series of questions with hypothetical DMTs with varying medication efficacies against 10%, 50%, and 90% chance of adverse side effects. Participants then selected on the MDMQ how likely they would be to take that particular medication. Probability discounting parameters were determined by the hyperbolic and GM hyperboloid models. AUC was also calculated for the three probabilities of side effect. Bruce et al. found that those who reported being non-adherent had higher $h$ values (i.e., were less likely to take medications) than those who were identified as adherent. This difference was consistent across all side effect values. AUC also consistently decreased (i.e., less adherence) based on increased risk of side effect. The
curves fit with the GM hyperboloid provided better fits to the data than hyperbolic model. AUC and demographic variables were used in a logistic regression model to predict medication adherence. AUC of 10% side effects was the only significant (p < .05) predictor of medication adherence.

Jarmolowicz et al. (2016) reanalyzed MDMQ data from Bruce et al. (2015) to calculate an effective probability for medication adherence where individuals would be indifferent ($EP_{50}$). To do this, the formula to determine ED50 was adapted to odds against $E\Theta_{50} = 1/h$, and then converted to EP50 via the formula $EP_{50} = 1 / (E\Theta_{50} + 1)$. A 2 x 3 repeated measures ANOVA determined that there were significant main effects of group and side effect, as well as interaction between group and side effect. They also extrapolated the likely times when an adherent individual would no longer take medication as per EP50, as well as the inverse of a non-adherent individual taking medications. Jarmolowicz et al. found that there were overlaps between groups when the $EP_{50}$ measure was used.

Jarmolowicz et al. (2017) used a modified version of the MDMQ (seven values of effectiveness and three severities) to assess medication adherence for persons with MS. Forty-two participants with MS completed this modified MDMQ. The Equation fit to the data at each of the three severities was $V = A / (1 + h\theta)$, where $A$ and $h$ were free parameters to be estimated. In this case, $A$ was considered the likelihood a participant was to take a medication with 100% effectiveness at various side effects. The model fit was good for all three severities at the individual level (median $R^2$ of .91, .92, and .94 for mild, moderate, and severe side effects respectively). The fitted value of $A$ also varied systematically by severity, with the unadjusted likelihoods decreasing as severity increased. They also found that AUC values were strongly correlated ($r > .5$) with self-reports of motivation to take DMTs.
Bruce, Jarmolowicz, et al. (2018) used an adapted version of the MDMQ (medical decision-making task; MDMT) and a shorter health decisions questionnaire (HDQ) to assess how participants with MS would take a hypothetical DMT based on effectiveness and side effects (e.g., mild, moderate, or severe). The MDMT consisted of 11 values ranging from 0.1% to 99.9% for probabilities of effectiveness and side effects. A total of 290 participants completed the MDMQ and 282 completed the HDQ. Repeated measures ANOVAs indicated differences on how participants were likely to take a drug based on side effect severity and effectiveness. Traditional discounting measures (e.g., $h$, AUC) were not included in this study.

Bruce, Bruce, et al. (2018) used the MDMT to assess decision-making in persons with MS. In this study, a three-dimensional model of probability discounting was used. The three-dimensional model was as follows, $V = U / [(1 + h_{se} \Theta_{se} S_{se}) x (1 + h_{e} \Theta_{e} S_{e})]$. This model consisted of the usual numerator (unadjusted value), with $A$ replaced with $U$ as the unadjusted likelihood of taking a medication at perfect efficacy. The discounting parameters for side effect and efficacy were $h_{se}$ and $h_{e}$ respectively. The parameters $\Theta_{se}$ and $\Theta_{e}$ were the odds against side effect and efficacy, and $S_{se}$ and $S_{e}$ were the sensitivity parameters of side effects and efficacy respectively. It should be noted that in this model $U$ was a free parameter and could take values that were not 100%. A total of 225 participants with MS completed the MDMT. Because of positive skew and kurtosis for discounting of side effect and efficacy, participants were divided into three groups, low (0–25th percentile), average (26–74th percentile) and high (75–100th percentile).

Participants who were in the low $h_{se}$ category were more likely to be adherent based on self-report, while participants categorized as high $h_{se}$ were less likely to be adherent. Those that were categorized as high $h_{e}$ performed more poorly than those in other groups on cognitive tests. The three-dimensional model performed well, with a mean $R^2$ of .9 ($SD = .09$).
Jarmolowicz, Reed, Bruce, et al. (2018) used the same three-dimensional model in conjunction with the MDMT as described in Bruce, Bruce, et al. (2018) for 299 persons with MS. Results from a repeated measures ANOVA indicated significant main effects of side-effect severity, side-effect probability, and DMT efficacy. The three-dimension model fits to mean participant likelihoods were high, with $R^2$ values of .96, .97, and .98 for mild, moderate, and severe side effects respectively. Significant differences were also identified for all estimated parameters based on side-effect severity.

Asgarova et al. (2017) examined the effects of framing on the probability discounting of taking a cardiovascular drug. Thirty-six Amazon Mechanical Turk (MTurk) workers were recruited and completed a series of questions regarding a hypothetical cardiovascular treatment. Questions were framed as either number of people out of 100 who have good health (positive frame) following taking a cardiovascular drug for a period of five years, or the number of people who experienced an adverse cardiovascular event (negative frame) in a five-year period. In both these cases the number of people who experienced good health or an adverse event was presented with the number of people who experienced either without taking the drug. These frames were tested against two types of side effect as a result of medication, frequent headaches or cold feet. In this study, indifference points were determined as the point when participants switched their decision from taking the drug to not taking it, or vice versa. Questions were presented using a titrating procedure to determine the indifference points for each participant at various risk/benefits. The probability discounting parameter $h$ was derived from these points using the hyperbolic model. AUC was also calculated for side effect and frame. Asgarova et al. found that while there was a significant difference between side effect of drug, there was not a significant difference between the positive and negative frames. Fits of the hyperbolic model to
participant probability curves were generally high, with median $R^2$ values ranging from .86 to .96 between the four conditions.

Jarmolowicz, Reed, Francisco, et al. (2018) applied discounting methodology to decisions to vaccinate based on social distance. Fifty participants were recruited from MTurk, 20 of which were parents. Only one parent did not vaccinate their child from this group. Participants were first required to create a “social network”, whereby they would imagine that the people closest to them as their closest relatives as 1 of 100, and someone as 100 units of distance as a virtual stranger. For parents, their child was a distance of 0. They were then required to name and state their relationships for the 3rd, 5th, 10, and 20th social distances. Following this, participants were given information about mild and moderate-to-severe side effects. They then completed a vaccine decision-making task which presented hypothetical vaccine with varying effects of protection, and participants then responded with the highest risk they were willing based on symptom severity. AUC was calculated at all social distances of 0, 5, 20, 50, and 100 for mild and moderate-to-severe side effects. In all cases, AUC was higher for mild side effects (i.e., people were more likely to vaccinate when risks were mild). For all data, four different discounting equations were compared for model fits. These were the exponential, hyperbolic, GM hyperboloid, and Rachlin hyperboloid models. Jarmolowicz, Reed, Francisco, et al. found that the Rachlin hyperboloid model provided the best fits to the data.

Nese et al. (2020) used discounting based procedures similar to Bruce et al. (2016) and Jarmolowicz, Reed, Francisco, et al. (2018) to determine compliance to COVID-19 containment measures. Participants were 931 Italians who responded to a survey between March 29th and April 4th of 2020 (i.e., following the initial and major damage of the COVID-19 pandemic in Italy). The questions asked Nese et al. (2020) consisted scenarios involving various risks of
contracting COVID-19 (10%, 50%, and 90%) and time in isolation (0, 7, 14, 30, 60, 90, 180 days). Participants would then select how acceptable terminating isolation was via a VAS. Participants also completed general anxiety metrics and psychological needs questionnaires. Discounting measures were assessed via AUC. Acceptable compliance was affected by risk of transmission, lower levels of transmission allowing for more permissible breaks of compliance over longer periods of time. AUC was correlated with perceived risk, but other measures were generally not correlated or weakly correlated with AUC ($r_s < .2$). At higher levels of risk, discounting did not appear to follow the traditional hyperbolic curve, but instead was more linear. Discounting at low risk of contracting COVID-19 followed a more typical discounting curve.

Rzeszutek et al. (under review) used discounting methodology to determine how individuals might remove a potentially cancerous tumor based on delay, risk, and surgical cost over two experiments. In the first experiment, 50 MTurk workers completed hypothetical monetary and medical decision-making questions. Monetary questions compared smaller-sooner values of a 99% change of $500 within a week against $1000 dollars with probabilities of 1%, 20%, 50%, 80% and 99% at delays of one week, six months, and two, five, and 15 years. These delays and probabilities were used for all monetary and medical decision-making questions. Participants would then use a VAS to determine how likely they were to choose between the smaller option and the delayed option. For monetary questions, participants were presented with gaining money at the previous values or losing money at those values. Following this, participants were then presented with scenarios where they had been diagnosed with a tumor that had a chance to become malignant after a given delay. Probabilities and delays were identical to the monetary decision-making questions. Participants would use a VAS to indicate how likely
they were to have the tumor surgically removed. Identical questions were presented but reframed as the tumor remaining benign, and probabilities inverted, thereby yielding mathematically equivalent cancer probabilities between frames. After completing the full set of remain benign or become malignant questions, participants were presented with questions that were identical to the become malignant scenario with the addition of a surgical costs of $100, $1,000, $10,000, and $100,000 to remove the tumor. Discounting was calculated using $AUC_{\text{log}}$ for curves at all probabilities and delays. Discounting values decreased as probability of cancer decreased and delay to cancer increased. Participants were more likely to remove a tumor if the situation was framed as becoming malignant rather than as remaining benign. The sign effect also occurred for monetary discounting, where gains were more steeply discounted than losses. The second experiment was similar to the first, with the exception that the monetary and “free” medical discounting questions were replaced with the tumor would remain benign scenario at the previously stated costs of removal. Results were similar to the first experiment, in that malignant frames produced higher endorsements of tumor removal, and that probability, delay, and cost affected decision-making. A novel metric, volume under the surface (VUS), was also calculated by generalizing AUC to three-dimensional discounting. Because odds against and large differences in delays were used, scales were log transformed resulting in $VUS_{\text{log}}$. This novel discounting measure was useful in identifying overall discounting at each surgical cost and frame. Framing and cost were still significantly different at all costs, but there was no significant interaction between frame and cost. The sign effect was consistent throughout all costs and probabilities. Monetary discounting did not appear to be related to medical discounting as based on $VUS_{\text{logs}}$. 
Summary of Health Discounting

As evidenced by the studies reviewed, there is much heterogeneity in the nature of the health questions used to assess health and medical discounting. For example, studies by Chapman (1996), Odum et al. (2002), Baker et al. (2003), and Friedel et al. (2016) used health questions that compared an immediate improvement followed by deterioration relative to a delayed improvement. Studies by Weatherly and colleagues and Sawicki and Markiewicz (2016) involved asking participants the percentage of treatment efficacy for an immediate option being equivalent to an effective treatment after a delay. All of these studies varied in whether a participant was required to provide an equivalent value for the alternative outcome, choose between outcomes, or an acceptable effectiveness. By contrast, studies by Bruce, Jarmolowicz, and colleagues, Nese et al. (2020), and Rzeszutek et al. (under review) asked participants how likely they’re going to accept a given medication or treatment, or the acceptability of some health-related behavior. Asgarova et al (2017) was different from studies by Bruce, Jarmolowicz, and colleagues, Nese et al. (2020), and Rzeszutek et al. (under review) as Asgarova et al. (2017) used a choice procedure to assess acceptability of a hypothetical treatment.

When it was assessed, the relationship between health-related discounting was not related to actual health behaviors (Chapman, 1996; Chapman et al. 2001; also see Chapman, 2005). Indeed, in the review by Story et al. (2014), monetary discounting was related to health behaviors, but health discounting was not. However, studies that assessed medication adherence did find relationships to real medical decisions and health discounting (Bruce et al., 2016; Jarmolowicz, et al., 2016). This could be due to the nature of the questions used to assess health discounting. Situations used were at times atypical to decisions a person may actually face. For example, one may never have to explicitly decide between 10 years of good health now followed
by bad health or 10 years of bad health now followed by 10 years of good health. And while some questions (Baker et al., 2003; Friedel et al. 2016; Odum et al. 2002) may be more similar to a decision one might face, because the situation was using AIDs-like symptoms, only a small proportion of the population are HIV positive (Centers for Disease Control and Prevention; CDC, 2020b) and therefore most people will not have direct experience with these types of situations. Contrast this with questions used by Bruce, Jarmolowicz, and colleagues, who used questions about a hypothetical DMT for those who actively use DMTs to treat a condition. The ecological validity of the discounting questions may be particularly relevant to determine a connection between monetary discounting and health-discounting, and potentially health-related behaviors.

**Identifying Appropriate Methods to Assess Medical Discounting**

While the reviewed studies used a variety of different methods (i.e., binary choice, FITB, MC, VAS) and response formats (i.e., equivalent worth, subjective likelihood) to derive indifference points, some formats appear to be more appropriate than others for particular research questions. For example, Smith and Hantula (2008) compared binary-choice methods to FITB procedures to assess generation of indifference points for monetary discounting. They argue that each method has its shortcomings but found that participants viewed FITB procedures were more ‘cognitively demanding.’ This appears to stem from the procedural requirement within FITB that participants must generate an equivalent value for the alternative option rather than choosing between two presented options. Although binary-choice procedures are dominant in discounting research, there is no methodological consensus with regard to discounting procedures (see Weatherly, 2014).
Lack of consensus aside, in the case of medical discounting, the studies by Bruce, Jarmolowicz, and colleagues, the VAS provided indifference points that fit hyperbola-based models of discounting quite well. This could be partly due to the similarity between the experimental task and the way a person may actually weigh two options. In this case, the options were to take or to not take a hypothetical DMT, where participant likelihood to take the DMT refers to subjective uncertainty of a participant’s behavior, in contrast to participant’s subjective value of a commodity. For example, Bruce et al. (2016) asked participants how likely they were to take a given DMT based on its side effects. If a participant reported 100% at efficacy versus side effect, that is equivalent to yes, 0% is equivalent to no, and ranges in between 0–100% represent subjective likelihood of engaging in a given behavior at that level of efficacy and side effect. It may be easier for participants to generate a percent likelihood of engaging in a behavior instead of identifying an equivalent DMT efficacy value relative to some other DMT efficacy with side effects due to fewer competing sources of control. In contrast, consider Chapman and Elstein (1995) where participants were asked to determine the equivalent number of years of full health after a delay would be needed to equal a year of full health. In these cases, participants have to identify what ‘full health’ means, but they also will probably consider their current age, situations that may occur within the next year, and what ‘full health’ after that delay means to them. It is substantially more effortful for participants to complete equivalence tasks when compare to a likelihood task. In the case of asking participants, “How likely are you to do X”, they only source of stimulus control is the question, and perhaps their covert verbal behavior as they produce a response. Compared to questions that ask for an equivalence of health following a delay, the question is exerting control on responding, but participants are also required to engage in more covert verbal behavior to generate conditioned stimuli relative to the question at hand.
For example, the question may evoke a statement such as, “What will I feel like after aging a year, and what does good health mean?” which in turn acts requires at least two more responses to be produced, one to the ‘feel after a year’, and another to ‘what does good health mean’. These new statements then act new sources of control, and so on. All these verbal responses are now new sources of stimulus control introduced following the initial equivalence-based discounting question. This could account for the previously mentioned “cognitively demanding” nature of the certain formats of discounting questions. More sources of control “compete” and decrease the likelihood of response being produced until enough stimuli and responses bring the terminal response to strength (i.e., the equivalent value).

Also, in the case of day-to-day medical decision-making, if an individual had a concerning symptom and was debating on seeking medical assistance, it is unlikely they would identify the equivalent value of some other symptom relative to their current symptom at some other time. They would probably be more likely to determine they will go, will not go, or debate on going to seek medical assistance for the symptom at hand. The debate and deliberation process (i.e., covert verbal behavior and problem solving) is captured in values from 0-100%. Also, in an attempt to adapt Rzeszutek et al. (under review) into an equivalence-based discounting scenario, it is not clear what a participant could be asked to provide an equivalence for a tumor becoming potentially cancerous after a delay. To ask participants, “You have a cancerous tumor now for some years, what is the cancerous tumor later for some years that would be equivalent” seems to be an impossible scenario and lacks face validity.

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3 A more detailed description of possible problem-solving during hypothetical-choice situations is outside the scope of the current paper, but book-length treatments of language and cognition from behavior-analytic perspectives are available (e.g., Hayes et al., 2001; Skinner, 1957).
Therefore, when considering medical decision-making, the method (i.e., binary choice, FITB, MC, VAS) may not matter, but the format of the response required by participants seems to be particularly important. Requiring identification of equivalent values, especially for medical decision-making, may not be appropriate. That is not to say equivalence-based discounting questions are inherently bad, but instead that they may be measuring some other variable rather than acting as a measurement of medical decision-making. How different methods affect indifference points is an empirical question, but a question that is outside of the scope of the current study. In the case of discounting specific medical decisions, the VAS is the most popular and best supported based on fits to hyperbola-based models of discounting.

The Present Study

For the majority of studies reviewed, health discounting situations presented were either unrealistic (e.g., hypothetical good health now or later; Chapman and colleagues), too specific (e.g., comparing AIDS-like symptoms now or later; Friedel et al., 2016; Odum et al., 2002) or used unique populations that have real experience with the hypothetical scenarios (e.g., patients with MS and their experience with DMTs; Bruce and colleagues). Other studies that examined somewhat more common treatments (e.g., acne treatment; Sawicki & Markiewicz, 2016; Weatherly & Terrell, 2014) only studied one or two types of treatments with more emphasis on cross-commodity effects rather than medical decision-making per se. These were also done in a way that some form of equivalence was requested rather than likelihood of choice. In studies that were asked participants how likely they were to take a hypothetical treatment (e.g., Asgarova et al., 2017; Bruce et al., 2015; Jarmolowicz, Reed, Francisco, et al., 2018), comparisons to traditional monetary discounting were not made. Because cross-commodity comparisons were done typically with unrealistic or unlikely scenarios, they may not have been fair comparisons
and could be why inconsistencies between health and monetary discounting occurred. In the
study by Rzeszutek et al. (under review), one experiment assessed differences in medical and
monetary decision making, but combined probability and delay discounting assessed via VUS
log, which makes it difficult to isolate why there was no apparent relationship between monetary and
medical decision-making. And while the magnitude effect between medical and monetary
discounting has been studied (Sawicki & Markiewicz, 2016; Weatherly & Terrell, 2014), the
discounting questions were based on equivalence of the alternative option rather than likelihood
of choosing an outcome. Therefore, the purpose of the current study was to assess the
discounting common health symptoms and their relationship between delay and probability
monetary discounting using methods with greater face validity.

In the case of the current study, the common symptoms to be assessed were cough,
headaches, and nausea, as everyone would likely have experienced these symptoms at least once
in their lifetimes. Participants were presented with questions asking how likely they are to seek a
medical professional after experiencing a given symptom for varying durations. This is because
it provides insight on general health-related decision-making, but it can also inform how
individuals avoid seeking help for mild but persistent symptoms which could be indicative of
more severe health problems (e.g., cancer). Delay and probability monetary discounting were
assessed and directly compared to determine if impulsivity or risk (as determined by monetary
discounting) has a relationship to this form of medical decision-making. Magnitude was assessed
for monetary discounting and medical discounting. In this way, correlations between the size of
the magnitude effect in monetary and medical decision-making can be explored. Lastly, much
like Rzeszutek et al. (under review) various cost of utilization was assessed at varying severities,
as this appears to be a key factor in health utilization. This allowed for assessing the relationship
between impulsive and risky decision-making relative to health-related scenarios that individuals are likely to experience or have experienced in their lives. Procedurally, all the medical decision-making questions in this study were novel, as well as the factors being compared between monetary and medical decision-making.

There were three experiments. The first assessed delay and probability discounting relative to symptom and severity. This allowed initial comparisons of risk, impulsivity, and medical decision-making. Because a health decision can be conceptualized as either a gain or a loss (i.e., a medical professional could either provide an individual with a treatment, or the medical professional could give a undesirable diagnosis), the sign effect was explored to determine if monetary losses or gains were related to medical decision-making. The second experiment assessed discounting of symptom severity relative to cost to access healthcare. The purpose of this experiment was to determine if there was an interaction between symptom, severity, and cost. It was expected that decision-making for high severity symptoms will be more resistant to effects of cost, but costs will still decrease the likelihood of seeking medical services much like Rzeszutek et al. (under review). This second experiment also acted as a partial replication of the first experiment. The third experiment compared delay and probability discounting, symptom severity, and cost to access healthcare. The purpose of the third study was to determine if and how the relationship between monetary discounting and medical decision-making change due to costs to the individual. This third experiment also served as a partial replication for the other two experiments.
General Methods

The following section describes common methods used across all three experiments. After covering these general methods, each experiment will have its own section for specific methods, results, and discussion.

Recruitment

Recruitment for each experiment consisted of Amazon Mechanical Turk (MTurk) workers, with 200 participants per study. To be able to access the survey, participants must (1) live in the United States, (2) have a 95% acceptance rate on MTurk, and (3) have completed over 100 HITs. The 95% acceptance rate and completed requirements are criteria that are standard benchmarks for quality assurance in academic survey research conducted on MTurk (Robinson et al., 2019). Each participant who successfully completed the survey and provided a valid code received $3.50. Those that failed the screener or did not provide a valid completion code were not compensated.

Survey Platform

The online platform Qualtrics was used to distribute the surveys.

Screener, Attention Check, and Captcha

Before accessing the experimental surveys, participants completed a brief percentage comprehension task using sliders (i.e., VAS; Appendix A). This brief task provided instructions and example of how to use the sliders, followed by four questions where participants are required to select the correct percentage. If a participant incorrectly answered these four questions, they were removed from the study. If a participant correctly answered these screener questions, the continued onto one of the three experimental surveys. At the end of the decision-making questions, an attention check was included to aid in removing potentially low-quality data. This
attention check question was “Would you rather have $1,000 immediately or $1 in a year”. If a participant selected a value of higher than 5 on the corresponding slider that ranged from 0 to 100, their data were excluded from analysis. Following removal of participant data based on the attention check, if a participant answered yes to the question involving underlying health conditions, but then said something like “No underlying health conditions” that would contradict their previous response, their data were also removed from the dataset. At the end of the survey but prior to the unique completion code, participants were required to complete a Captcha. This was to decrease the likelihood of bots (i.e., non-human automated scripts) from completing the survey and gaining compensation.

Demographics, and General Health Questions

Following completion of the experimental questions, all participants completed a series demographic and health-related questions. These consisted of general concern related to the symptoms and severities, health insurance status, smoking assessed by the Fagerström Test for Nicotine Dependence (Heatherton et al., 1991), general health by the Short Form Health Survey (SF-12; Ware et al., 1996), trust in doctors (Dugan et al., 2005), delaying/avoiding real medical procedures due to cost, and other general demographics (See Appendices C–I).

Common Discounting Parameters Across Experiments

For all experiments, common values were used to assess decision-making and will be discussed here. All questions involving monetary delays assessed decision-making between a smaller, sooner ($500 or $5,000) amount and a larger, later ($1,000 or $10,000) amount at delays to the larger amount at 1 day, 1 month, 6 months, 1 year, and 2 years. All questions involving monetary choices between a small, certain ($500 or $5,000) amount and a larger, uncertain ($1,000 or $10,000) amount and probabilities of receiving the uncertain amount of 99%, 80%,
50%, 20%, and 1%. All questions involving health decision-making used duration of symptoms experienced at 6 hours, 1 day, 1 week, 1 month, and 6 months. In all cases, delays and durations were always presented in an ascending order, whereas probabilities were presented in a descending order. In the case of health discounting, experienced symptoms were always headache, nausea, or coughing. See Appendix J for examples and values used across experiments.

Data Analysis

For all data manipulation and statistical calculations, the statistical programming environment R 4.03 (R Core Team, 2020) and data.table package (Dowle & Srinivasan, 2020) were used. To calculate decision-making during tasks, $\text{AUC}_{\text{ord}}$ was calculated for all conditions. Indifference points at a given delay, probability, or duration of symptoms were simply the participant response at the delay, probability, or duration of symptoms assessed. To make appropriate comparisons between loss and gain monetary frames, indifference points from loss frame questions were subtracted from 100 to produce a descending curve rather than an ascending curve produced based on the VAS methods used. Because $\text{AUC}_{\text{ord}}$ is a proportion, beta regression was used as the beta distribution is better able to handle proportions when compared to linear models with assumptions of normally distributed data. Because of the repeated measures nature of the study, mixed-effects beta regressions were used with the variables of interest (i.e., frame, probability, delay, cost) as fixed effects and participants as the random effect. Mixed-effects beta regressions were conducted using the glmmTMB package (Brooks et al., 2017). Because the beta regression implementation in the glmmTMB package cannot handle explicit 0s and 1s, those values were converted to 0.0001 and 0.9999 respectively. To assess the overall significance of fixed effects, Wald tests using type-II sums of squares were conducted for
all mixed-model regressions via the car package (Fox & Weisberg, 2019). In all cases, regressions included interactions between factors when interactions could be assessed. Spearman correlations and corrections for multiple comparisons were conducted using the psych package (Revelle, 2020). The Holm-Bonferroni method was used to correct for multiple comparisons. To determine associations between demographic factors and their relationship to monetary discounting and health decision-making, MANOVAs with Pillai’s Trace were conducted with the car package using general linear models and separated by delay, probability, and/or symptom when applicable. All MANOVAs included age, socioeconomic status (SES), gender, ethnicity, smoking status, health insurance status, trust in doctors, the physical component score (PCS) and mental component summary (MCS) measures from the SF-12, underlying health condition, and having avoided/delayed seeking healthcare due to cost.

To compare different models of discounting, Gilroy et al.’s (2017) model selector was used to determine the most probable model (i.e., noise, exponential, hyperbolic, GM hyperboloid, Rachlin hyperboloid). For questions involving loss frames and health questions, participant response values were inverted so that the values across times or probabilities were descending. This is because typical discounting equations assume a decrease in value over time, rather than an increase in value as expected in the health decision-making questions. For posterity, the Johnson and Bickel (JB; 2008) algorithm to assess discounting data was applied to all data paths that were included following screening. The two criteria assessed via the JB algorithm to assess non-systematic discounting are that no indifference point is higher than 20% of the total subjective value than the previous indifference point (bounce), and that the first indifference point is at least 10% of the total subjective value higher than the last indifference point (sensitivity). No data were removed if they failed to meet either or both JB criteria.
For demographic variables, income and education were combined into a three-tier SES indicator based on Sheffer et al., (2017). Income and education were each assigned a value, added together, and then combined to create the three tiers. This SES scale has 1 as the lowest SES and 3 as the highest SES. Reported gender was sorted into “male”, “female”, or “other”. Ethnicity was grouped into “Caucasian”, “Asian”, “Black/African”, “Hispanic/Latin”, and “other”. Trust in doctors was aggregated across the five questions into a single value. Health insurance status was converted to either a participant having coverage (i.e., “yes”) or not (i.e., “no”).

Experiment 1

Methods

The first experiment consisted of delay and probability monetary discounting scenarios, followed by experienced symptoms scenarios. First, participants were randomly assigned to complete either delay or probability discounting for monetary outcomes. In all cases, they were always presented with discounting questions first of small monetary gains ($500 vs $1,000), then large monetary gains ($5,000 vs $10,000), then small monetary losses ($500 vs $1,000), and finally large monetary losses ($5,000 vs $10,000). After completing the delay or probability discounting questions, they then completed the alternative. For example, if they first completed a set of probability discounting questions, they then completed a set of delay discounting questions and vice versa. After completing both delay and probability discounting of monetary outcomes, participants completed health decision-making questions. Order of health symptoms (coughing, headache, and nausea) was randomly determined but the severity of symptoms (mild, moderate, and severe) was always presented as increasing severities for a given symptom. For example, if a participant completed decision-making questions regarding headaches first, they would complete
a set of questions with mild headache severity over ascending durations, then moderate headache severity, and finally severe headache severity. Therefore, there were a total of 40 monetary discounting questions and 35 health decision-making questions participants in Experiment 1 completed.

**Results**

*Screening, Duration, and Estimated Compensation*

Following screening there were data from 165 participants were deemed as being usable (82.5%). Median time to survey completion was 16.67 minutes (min = 5.53, max = 69.82). Therefore, compensation based on median time to completion was $12.60/hr.

**Demographics**

The participant demographics for Experiment 1 can be found in Table 1. The majority of participants identified as male (61.2%) and white (74.5%). Mean age was 39.2. Most had some form of health insurance coverage (86.1%) and had employment outside of MTurk (78.8%).

<table>
<thead>
<tr>
<th>Table 1. Experiment 1 Demographics</th>
<th>n/mean</th>
<th>%/SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age</strong></td>
<td>39.2</td>
<td>11.1</td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>101</td>
<td>61.2</td>
</tr>
<tr>
<td>Female</td>
<td>64</td>
<td>38.8</td>
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<tr>
<td>Other</td>
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<td>0</td>
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<tr>
<td><strong>Ethnicity</strong></td>
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<td></td>
</tr>
<tr>
<td>Caucasian</td>
<td>123</td>
<td>74.5</td>
</tr>
<tr>
<td>Asian</td>
<td>18</td>
<td>10.9</td>
</tr>
<tr>
<td>Black/African</td>
<td>14</td>
<td>8.5</td>
</tr>
<tr>
<td>Hispanic/Latin</td>
<td>10</td>
<td>6.1</td>
</tr>
<tr>
<td>Other</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td><strong>Other Employment</strong></td>
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<td></td>
</tr>
<tr>
<td>No</td>
<td>35</td>
<td>21.2</td>
</tr>
<tr>
<td>Yes</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td><strong>SES Bracket</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-Low</td>
<td>12</td>
<td>7.3</td>
</tr>
<tr>
<td>2-Medium</td>
<td>47</td>
<td>28.5</td>
</tr>
</tbody>
</table>
Health Insurance
Medicaid/Medicare 40 24.2
Insured 88 53.3
Family/Spouse 14 8.5
Uninsured 23 13.9
Lost Health Insurance Yes 1 0.6
Smoker Yes 35 21.2
SF-12
PCS 16.9 3
MCS 18 3.1
Delayed Healthcare Yes 66 40
Avoided Healthcare Yes 63 38.2
Either Avoided or Delayed Yes 73 44.2
Underlying Conditions Yes 42 25.5
Trust in Doctors 16.5 4.2

Note. For discrete variables, the number of participants and percentage of sample are included. For continuous variables, mean and SD are included. SF-12 maximum scores are 20 and 27 for PCS (Physical Component Summary) and MCS (Multiple Component Summary) respectively. Trust in doctors maximum score is 25. Both lost employment and healthcare refer to losing either due to the COVID-19 pandemic. SES strata were determined by combining income and education into a composite score based on Sheffer et al. (2017).

Monetary Discounting

Table 2 is correlation matrix of Spearman correlations of all behavioral outcomes (i.e., monetary discounting and health decision-making) calculated by AUC_{ord} in Experiment 1. Delay discounting measures were generally strongly correlated with each other, while not correlated with probability discounting measures. There were some small correlations between delay discounting of losses and probability discounting, but after corrections for multiple comparisons only one significant relationship remained between delay discounting of large losses and
probability discounting of large losses. For delay discounting, there was a significant difference for the loss frame, $\chi^2(1) = 37.09, p < .0001$, and magnitude, $\chi^2(1) = 15.59, p < .0001$. There was a non-significant interaction between loss and magnitude, $\chi^2(1) = 3.16, p = .0753$. Both loss and large magnitudes increased $AUC_{ord}$ (i.e., decreased discounting). For probability discounting, only the loss frame was significant, $\chi^2(1) = 165.22, p < .0001$, where as there was no statistical evidence of the magnitude effect, $\chi^2(1) = 0.51, p = .4731$, or interaction between loss and magnitude, $\chi^2(1) = 0.41, p = .5206$. Much like for delay discounting, the loss frame increased $AUC_{ord}$ of probability discounting (i.e., decreased discounting). Figure 1 is a boxplot of $AUC_{ord}$ of delay and probability discounting by loss frame and magnitudes.
Table 2. Correlation Matrix of Behavioral Measures Based on AUCords from Experiment 1

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
<th>17</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. DD S+</td>
<td>0.89**</td>
<td>0.51**</td>
<td>0.48**</td>
<td>0.09</td>
<td>-0.08</td>
<td>0.12</td>
<td>0.19</td>
<td>-0.28*</td>
<td>-0.23</td>
<td>-0.14</td>
<td>-0.39**</td>
<td>-0.34**</td>
<td>-0.18</td>
<td>-0.22</td>
<td>-0.16</td>
<td>-0.07</td>
<td></td>
</tr>
<tr>
<td>2. DD L+</td>
<td>0.89**</td>
<td>0.58**</td>
<td>0.58**</td>
<td>0.08</td>
<td>-0.08</td>
<td>0.09</td>
<td>0.18</td>
<td>-0.33**</td>
<td>-0.27*</td>
<td>-0.15</td>
<td>-0.44**</td>
<td>-0.42**</td>
<td>-0.2</td>
<td>-0.24</td>
<td>-0.2</td>
<td>-0.05</td>
<td></td>
</tr>
<tr>
<td>3. DD S-</td>
<td>0.51**</td>
<td>0.58**</td>
<td>0.77**</td>
<td>0.01</td>
<td>-0.09</td>
<td>0.16</td>
<td>0.24</td>
<td>-0.36**</td>
<td>-0.25</td>
<td>-0.19</td>
<td>-0.44**</td>
<td>-0.4**</td>
<td>-0.19</td>
<td>-0.25</td>
<td>-0.18</td>
<td>-0.03</td>
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</tr>
<tr>
<td>4. DD L-</td>
<td>0.48**</td>
<td>0.58**</td>
<td>0.77**</td>
<td>-0.03</td>
<td>-0.12</td>
<td>0.18</td>
<td>0.27*</td>
<td>-0.28*</td>
<td>-0.22</td>
<td>-0.09</td>
<td>-0.41**</td>
<td>-0.35**</td>
<td>-0.15</td>
<td>-0.2</td>
<td>-0.17</td>
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</tr>
<tr>
<td>5. PD S+</td>
<td>0.09</td>
<td>0.08</td>
<td>0.01</td>
<td>-0.03</td>
<td>0.77**</td>
<td>-0.19</td>
<td>-0.1</td>
<td>0.08</td>
<td>0.14</td>
<td>0.09</td>
<td>0</td>
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<tr>
<td>6. PD L+</td>
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<td>-0.08</td>
<td>-0.09</td>
<td>-0.12</td>
<td>0.77**</td>
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</tr>
<tr>
<td>7. PD S-</td>
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<td>0.09</td>
<td>0.16*</td>
<td>0.18*</td>
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<td>8. PD L-</td>
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<td>0.18*</td>
<td>0.24**</td>
<td>0.27**</td>
<td>-0.1</td>
<td>-0.1</td>
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<td>-0.1</td>
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<tr>
<td>9. Mi H</td>
<td>-0.28**</td>
<td>-0.33**</td>
<td>-0.36**</td>
<td>-0.28**</td>
<td>0.08</td>
<td>0.06</td>
<td>-0.11</td>
<td>-0.17*</td>
<td>0.82**</td>
<td>0.71**</td>
<td>0.7**</td>
<td>0.72**</td>
<td>0.59**</td>
<td>0.7**</td>
<td>0.65**</td>
<td>0.48**</td>
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<tr>
<td>10. Mo H</td>
<td>-0.23**</td>
<td>-0.27**</td>
<td>-0.25**</td>
<td>-0.22**</td>
<td>0.14</td>
<td>0.14</td>
<td>-0.01</td>
<td>-0.04</td>
<td>0.82**</td>
<td>0.82**</td>
<td>0.6**</td>
<td>0.68**</td>
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</tr>
<tr>
<td>11. Se H</td>
<td>-0.14</td>
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<td>-0.19*</td>
<td>-0.09</td>
<td>0.09</td>
<td>0.07</td>
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<td>-0.03</td>
<td>0.71**</td>
<td>0.82**</td>
<td>0.5**</td>
<td>0.61**</td>
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</tr>
<tr>
<td>12. Mi C</td>
<td>-0.39**</td>
<td>-0.44**</td>
<td>-0.44**</td>
<td>-0.41**</td>
<td>0</td>
<td>0.06</td>
<td>-0.03</td>
<td>-0.16*</td>
<td>0.7**</td>
<td>0.6**</td>
<td>0.5**</td>
<td>0.87**</td>
<td>0.66**</td>
<td>0.63**</td>
<td>0.6**</td>
<td>0.41**</td>
<td></td>
</tr>
<tr>
<td>13. Mo C</td>
<td>-0.34**</td>
<td>-0.42**</td>
<td>-0.44**</td>
<td>-0.35**</td>
<td>-0.03</td>
<td>-0.04</td>
<td>-0.02</td>
<td>-0.11</td>
<td>0.72**</td>
<td>0.68**</td>
<td>0.61**</td>
<td>0.87**</td>
<td>0.81**</td>
<td>0.67**</td>
<td>0.67**</td>
<td>0.53**</td>
<td></td>
</tr>
<tr>
<td>14. Se C</td>
<td>-0.18</td>
<td>-0.2*</td>
<td>-0.19*</td>
<td>-0.15</td>
<td>0.02</td>
<td>0.03</td>
<td>-0.03</td>
<td>-0.07</td>
<td>0.59**</td>
<td>0.65**</td>
<td>0.66**</td>
<td>0.81**</td>
<td>0.61**</td>
<td>0.7**</td>
<td>0.7**</td>
<td>0.7**</td>
<td></td>
</tr>
<tr>
<td>15. Mi N</td>
<td>-0.22**</td>
<td>-0.24**</td>
<td>-0.25**</td>
<td>-0.22**</td>
<td>0.03</td>
<td>-0.01</td>
<td>-0.13</td>
<td>-0.1</td>
<td>0.7**</td>
<td>0.63**</td>
<td>0.6**</td>
<td>0.63**</td>
<td>0.67**</td>
<td>0.61**</td>
<td>0.81**</td>
<td>0.63**</td>
<td></td>
</tr>
<tr>
<td>16. Mo N</td>
<td>-0.16*</td>
<td>-0.2*</td>
<td>-0.18*</td>
<td>-0.17*</td>
<td>0.04</td>
<td>0</td>
<td>-0.06</td>
<td>-0.03</td>
<td>0.65**</td>
<td>0.69**</td>
<td>0.71**</td>
<td>0.6**</td>
<td>0.67**</td>
<td>0.7**</td>
<td>0.81**</td>
<td>0.77**</td>
<td></td>
</tr>
<tr>
<td>17. Se N</td>
<td>-0.07</td>
<td>-0.05</td>
<td>-0.03</td>
<td>0.04</td>
<td>-0.06</td>
<td>-0.09</td>
<td>0.01</td>
<td>0.03</td>
<td>0.48**</td>
<td>0.57**</td>
<td>0.72**</td>
<td>0.41**</td>
<td>0.53**</td>
<td>0.7**</td>
<td>0.63**</td>
<td>0.77**</td>
<td></td>
</tr>
</tbody>
</table>

Figure 1. Boxplot of Experiment 1 Monetary Discounting

**Ex 1 Monetary Discounting**

- Small Gain
- Large Gain
- Small Loss
- Large Loss

**Note.** Boxplots of $\text{AUC}_{\text{ord}}$ of delay and probability discounting. Boxes represent the middle 50% of the distribution, white squares represent the mean, horizontal black lines represent the median. Whiskers are 1.5 x IQR. Order for both delay and probability are by gains (small then large) and losses (small then large). Higher values of delay $\text{AUC}_{\text{ord}}$ indicate less impulsive decision-making, whereas higher values of probability $\text{AUC}_{\text{ord}}$ indicate greater risky decision-making. Magnitude and frame were significantly different for delay discounting, but only frame was significant for probability discounting. There was no significant interaction between frame and magnitude for either delay or probability discounting.

The results of Gilroy et al.’s (2017) model selection process for each condition in Experiment 1 can be found in Table 3. For monetary discounting, the Rachlin model was heavily favored over other models (35.8%–76.4% of data paths), with the noise model being the second
most favored (14.5%–57.6%). For delay discounting, loss frames had a higher proportion of noise models (i.e., straight lines). Figure 2 are line graphs of the median points for monetary discounting.

Table 3. Experiment 1 Model Selection Results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Noise</th>
<th>Exponential</th>
<th>Hyperbolic</th>
<th>Green-Myerson</th>
<th>Rachlin</th>
</tr>
</thead>
<tbody>
<tr>
<td>DD S +</td>
<td>24.8(41)</td>
<td>13.3(22)</td>
<td>4.8(8)</td>
<td>4.8(8)</td>
<td>52.1(86)</td>
</tr>
<tr>
<td>DD L +</td>
<td>37.6(62)</td>
<td>7.9(13)</td>
<td>4.2(7)</td>
<td>2.4(4)</td>
<td>47.9(79)</td>
</tr>
<tr>
<td>DD S -</td>
<td>51.5(85)</td>
<td>6.1(10)</td>
<td>4.2(7)</td>
<td>2.4(4)</td>
<td>35.8(59)</td>
</tr>
<tr>
<td>DD L -</td>
<td>57.6(95)</td>
<td>4.2(7)</td>
<td>6.1(10)</td>
<td>2.4(4)</td>
<td>29.7(49)</td>
</tr>
<tr>
<td>PD S +</td>
<td>18.2(30)</td>
<td>2.4(4)</td>
<td>1.2(2)</td>
<td>1.8(3)</td>
<td>76.4(126)</td>
</tr>
<tr>
<td>PD L +</td>
<td>14.5(24)</td>
<td>4.2(7)</td>
<td>3.6(6)</td>
<td>1.8(3)</td>
<td>75.8(125)</td>
</tr>
<tr>
<td>PD S -</td>
<td>21.2(35)</td>
<td>7.3(12)</td>
<td>6.7(11)</td>
<td>1.8(3)</td>
<td>63(104)</td>
</tr>
<tr>
<td>PD L -</td>
<td>17(28)</td>
<td>7.9(13)</td>
<td>3(5)</td>
<td>3.6(6)</td>
<td>68.5(113)</td>
</tr>
</tbody>
</table>

| Mi H     | 8.5(14) | 9.7(16) | 8.5(14) | 16.4(27) | 57(94) |
| Mo H     | 10.3(17) | 11.5(19) | 12.7(21) | 13.9(23) | 51.5(85) |
| Se H     | 11.5(19) | 9.7(16) | 10.9(18) | 7.9(13) | 60(99) |
| Mi C     | 10.3(17) | 11.5(19) | 12.1(20) | 14.5(24) | 51.5(85) |
| Mo C     | 6.7(11) | 10.9(18) | 15.2(25) | 15.8(26) | 51.5(85) |
| Se C     | 10.9(18) | 13.3(22) | 9.7(16) | 8.5(14) | 57.6(95) |
| Mi N     | 10.3(17) | 10.9(18) | 12.7(21) | 13.3(22) | 52.7(87) |
| Mo N     | 9.1(15) | 9.7(16) | 7.3(12) | 13.3(22) | 60.6(100) |
| Se N     | 14.5(24) | 8.5(14) | 10.3(17) | 15.8(26) | 50.9(84) |
| Total    | 19.7(552) | 8.8(246) | 7.8(220) | 8.3(232) | 55.4(1555) |

Figure 2. Line Graphs of Experiment 1 Monetary Discounting

Delay Discounting

- Small Gain
- Large Gain
- Small Loss
- Large Loss

Probability Discounting

- Small Gain
- Large Gain
- Small Loss
- Large Loss

Note. Line graphs of delay (left panel) and probability (right panel) discounting in Experiment 1. Y-axis represents the likelihood a participant would choose the ‘better option’ (i.e., larger reward or smaller loss) for both delay and probability discounting. Delays are in days and probabilities are in percent chance of larger outcome. Note that percent chance is in descending rather than ascending order to allow for comparisons with delay discounting.

The JB assessment of discounting can be found in Table 4 based on condition. Few data paths for monetary discounting were identified as having bounce (1.2% – 10.3%), while more were identified as not meeting the sensitivity criteria (13.9%–59.4%). The three highest conditions for not meeting sensitivity criteria were the loss frames for delay discounting and the
large magnitude for delay discounting. Generally, there was a low percentage of data paths that failed both JB criteria (0.6%–8.5%) for monetary discounting.

**Table 4. Experiment 1 Johnson & Bickel Criteria**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Bounce</th>
<th>Sensitivity</th>
<th>Both</th>
</tr>
</thead>
<tbody>
<tr>
<td>DD S +</td>
<td>2.4(4)</td>
<td>25.5(42)</td>
<td>1.2(2)</td>
</tr>
<tr>
<td>DD L +</td>
<td>1.2(2)</td>
<td>40.6(67)</td>
<td>0.6(1)</td>
</tr>
<tr>
<td>DD S -</td>
<td>5.5(9)</td>
<td>52.1(86)</td>
<td>4.8(8)</td>
</tr>
<tr>
<td>DD L -</td>
<td>4.8(8)</td>
<td>59.4(98)</td>
<td>4.8(8)</td>
</tr>
<tr>
<td>PD S +</td>
<td>6.7(11)</td>
<td>17(28)</td>
<td>4.8(8)</td>
</tr>
<tr>
<td>PD L +</td>
<td>7.3(12)</td>
<td>13.9(23)</td>
<td>4.8(8)</td>
</tr>
<tr>
<td>PD S -</td>
<td>10.3(17)</td>
<td>20(33)</td>
<td>7.3(12)</td>
</tr>
<tr>
<td>PD L -</td>
<td>10.3(17)</td>
<td>16.4(27)</td>
<td>8.5(14)</td>
</tr>
<tr>
<td>Mi H</td>
<td>3(5)</td>
<td>9.7(16)</td>
<td>3(5)</td>
</tr>
<tr>
<td>Mo H</td>
<td>3.6(6)</td>
<td>10.3(17)</td>
<td>3(5)</td>
</tr>
<tr>
<td>Se H</td>
<td>3(5)</td>
<td>13.9(23)</td>
<td>3(5)</td>
</tr>
<tr>
<td>Mi C</td>
<td>4.2(7)</td>
<td>12.7(21)</td>
<td>3(5)</td>
</tr>
<tr>
<td>Mo C</td>
<td>3(5)</td>
<td>7.9(13)</td>
<td>3(5)</td>
</tr>
<tr>
<td>Se C</td>
<td>3.6(6)</td>
<td>13.3(22)</td>
<td>2.4(4)</td>
</tr>
<tr>
<td>Mi N</td>
<td>4.8(8)</td>
<td>12.1(20)</td>
<td>4.8(8)</td>
</tr>
<tr>
<td>Mo N</td>
<td>3.6(6)</td>
<td>12.7(21)</td>
<td>3.6(6)</td>
</tr>
<tr>
<td>Se N</td>
<td>4.2(7)</td>
<td>18.2(30)</td>
<td>3(5)</td>
</tr>
<tr>
<td>Total</td>
<td>4.8(135)</td>
<td>20.9(587)</td>
<td>3.9(109)</td>
</tr>
</tbody>
</table>


For delay discounting, only the SF-12 PCS was found to be statistically significant, $V = 0.11, F(4, 147) = 4.41, p = .0022$. For probability discounting, only ethnicity was found to be a significant, $V = 0.15, F(12, 447), p = 0.023$. No other demographic variables were found to be significantly associated with delay or probability discounting. Table 5 contains aggregated parameter estimates from all regressions used in the MANOVA.
Table 5. Experiment 1 Aggregated Relationships with Demographics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Condition</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DD</td>
<td>PD</td>
<td>Cough</td>
<td>Headache</td>
<td>Nausea</td>
</tr>
<tr>
<td>Age</td>
<td>0.0014</td>
<td>-0.0002</td>
<td>-0.0022</td>
<td>-0.001</td>
<td>-0.0014</td>
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<tr>
<td>SES-2</td>
<td>-0.0354</td>
<td>0.0687</td>
<td>0.0436</td>
<td>0.063</td>
<td>-0.0206</td>
</tr>
<tr>
<td>SES-3</td>
<td>-0.1374</td>
<td>0.015</td>
<td>0.1013</td>
<td>0.1016</td>
<td>0.026</td>
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<td>Gen-Male</td>
<td>0.0029</td>
<td>-0.0027</td>
<td>0.042</td>
<td>0.0715</td>
<td>0.0425</td>
</tr>
<tr>
<td>Eth-Asian</td>
<td>-0.0602</td>
<td><strong>0.0457</strong></td>
<td>0.0541</td>
<td>0.0072</td>
<td>0.0148</td>
</tr>
<tr>
<td>Eth-Hispanic/Latin</td>
<td>0.0234</td>
<td><strong>-0.0101</strong></td>
<td>-0.129</td>
<td>-0.097</td>
<td>-0.1487</td>
</tr>
<tr>
<td>Eth-Black/African</td>
<td>-0.2396</td>
<td><strong>0.0441</strong></td>
<td>0.1692</td>
<td>0.161</td>
<td>0.0698</td>
</tr>
<tr>
<td>Smoker</td>
<td>-0.0116</td>
<td>-0.019</td>
<td>-0.0093</td>
<td>0.0002</td>
<td>-0.0155</td>
</tr>
<tr>
<td>Insured</td>
<td>0.1067</td>
<td>0.01</td>
<td>0.028</td>
<td>0.052</td>
<td>0.079</td>
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<tr>
<td>Doctor Trust</td>
<td>-0.005</td>
<td>0.0004</td>
<td><strong>0.0112</strong></td>
<td>0.0071</td>
<td><strong>0.008</strong></td>
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<tr>
<td>SF12-PCS</td>
<td><strong>0.0379</strong></td>
<td>-0.0034</td>
<td><strong>-0.0175</strong></td>
<td>-0.017</td>
<td>-0.0079</td>
</tr>
<tr>
<td>SF12-MCS</td>
<td>-0.0139</td>
<td>0.0011</td>
<td>0.0115</td>
<td>0.0053</td>
<td>0.0013</td>
</tr>
<tr>
<td>Underlying Condition</td>
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<td>0.0074</td>
<td>-0.0267</td>
<td>-0.0322</td>
</tr>
<tr>
<td>Avoided/Delayed Healthcare</td>
<td>0.0491</td>
<td>-0.0284</td>
<td>0.0032</td>
<td>0.0029</td>
<td>0.0153</td>
</tr>
</tbody>
</table>

Note. Averaged parameter estimates from all linear regressions used in the MANOVA. **Bold**: Overall factors that were identified as significant from the MANOVA, not individual estimates. DD: Delay discounting. PD: Probability discounting. Cough, Headache, Nausea: Overall medical decision-making for respective symptom. Dashed line separates monetary discounting from medical decision-making. Reference points for SES, gender, and ethnicity are SES-1, female, and Caucasian respectively. SF-12 PCS: Physical Component Summary scores. SF-12 MCS: Mental Component Summary Scores.

**Health Decision-Making**

Table 2 is a table of Spearman correlations for all behavioral measures for Experiment 1. Generally, responses to health-related questions were highly correlated with responses to other health-related questions. That is, those that were more likely to seek a medical professional for one symptom were likely to seek a medical professional for another. This pattern was consistent for severities across symptom as well. While decision-making for health was most correlated within a symptom rather than between, the as severity increased within a symptom, the association with other severities of that symptom decreased. For medical decision-making, severity, $\chi^2(2) = 635.60$, $p < .0001$, and symptom, $\chi^2(2) = 93.66$, $p < .0001$, were significant factors. There was no significant interaction between the two, $\chi^2(5) = 3.02$, $p = .5537$. As
symptom severity increased, likelihood of seeking a medical professional increased, while seeking treatment for coughing was lowest, followed by headache, and finally nausea. Figure 3 is a boxplot of AUC$_{ord}$ of medical decision-making by symptom and severity.

*Figure 3. Boxplot of Experiment 1 Health Decision-Making*

*Note.* Boxplots of AUC$_{ord}$ of health decision-making questions in Experiment 1. Boxes represent the middle 50% of the distribution, white squares represent the mean, horizontal black lines represent the median. Whiskers are 1.5 x IQR. Symptoms are ordered by cough, headache, and nausea. Severity increases from left to right. Higher values of AUC$_{ord}$ indicate increased likelihood to seek healthcare. Symptom and severity were statistically significant factors, but there was no significant interaction between them.
Model selection for health decision-making can be found in Table 3. The Rachlin model was favored in all cases (50.9%–60.6%), with fairly similar proportions between the other models. JB criteria failures were generally low for bounce (3%–4.8%), sensitivity (7.9%–18.2%), and both (2.4%–4.8%). As severity increased, JB failures of sensitivity also increased. Figures 4, 5, and 6 are line graphs of health decision-making across duration a symptom was experienced for cough, headaches, and nausea respectively. Experimental health decision-making JB failures can be found in Table 4.

*Figure 4. Line Graph of Experiment 1 Medical Decision-Making – Cough*
Note. Line graph of median medical decision-making for cough in Experiment 1. Y-axis is the median likelihood of seeking a medical professional. X-axis is duration the symptom has persisted in days.

Figure 5. Line Graph of Experiment 1 Medical Decision-Making – Headaches

Note. Line graph of median medical decision-making for headaches in Experiment 1. Y-axis is the median likelihood of seeking a medical professional. X-axis is duration the symptom has persisted in days.
Delay discounting for gains and losses was significantly related to most health decision-making scenarios, with an inverse relationship between seeking health treatment and monetary discounting. That is, those who might be considered as “more impulsive” based on monetary discounting were more likely to seek treatment earlier than those who were “less impulsive” based on monetary discounting. There did not appear to be a clear relationship between sign of
delay discounting and health decision-making. Riskiness (i.e., probability discounting) did not seem to be related to health decision-making. After accounting for multiple comparisons, this generally seemed to be consistent across magnitudes and gain/loss frames. A general trend that occurred is that as severity increased, the strength of the relationship decreased. After correcting for multiple comparisons, the associations between delay discounting and nausea were no longer significant.

For demographic factors associated with medical decision-making, trust in doctors, $V = 0.06$, $F(3, 148) = 3.12, p = .028$, and SF-12 PCS, $V = 0.07$, $F(3, 148) = 3.79, p = .012$ were the only significant factors for coughs. For headaches, only gender, $V = .06, F(3, 148) = 3.08, p = .029$, was a significant factor. Lastly, gender, $V = .05, F(3, 148) = 2.84, p = .04$, and trust in doctors, $V = .07, F(3, 148) = 3.92, p = .01$, were significantly factors for nausea. Aggregated parameter estimates for Experiment 1 can be found in Table 5.

**Discussion**

Generally, results of previous discounting were replicated regarding gains and losses for delayed and probabilistic outcomes. Loss frames decreased impulsivity and increased riskiness, although the magnitude effect was not seen for probability discounting. For health decision-making, there was both a commodity specific effect between symptoms, and severities affect decision-making in predictable ways. Impulsivity was related to seeking medical help, in that those who were more impulsive (i.e., steeper discounters) were more likely to seek help sooner based on duration of experienced symptom. Probability discounting was not related to either delay discounting or medical decision-making. There were few associations with medical decision-making and demographic variables, although gender, physical health, and trust in doctors seem to be moderators of decision-making.
Experiment 2

Methods

The second experiment was similar to the health decision-making section in Experiment 1, with the addition of an added cost ($10, $100, $1000) to accessing a healthcare professional and the removal of monetary discounting questions. For example, a question was presented as “You have been experiencing X Y for the past Z. It will cost you A to see a healthcare professional. How likely are you to contact or see a healthcare professional for your symptoms?” In this example, X represents a severity (i.e., mild, moderate, severe), Y represents a symptom (i.e., headache, nausea, cough) and A is a cost (i.e., $10, $100, $1000). Order of symptoms were randomized, but severities and costs were always be presented in an ascending order for that symptom. For example, if nausea is the first symptom randomly selected, cost at $10 was assessed at increasing durations at increasing severities, then cost at $100 was assessed at increasing durations and increasing severities, and finally cost at $1000 was assessed at increasing durations and increasing severities. This resulted in a total of 90 discounting questions for Experiment 2.

Results

Survey Duration and Screening

Following screening there were data from 146 participants that were deemed as being usable (73.0%). Median time to survey completion was 16.39 minutes (min = 6.92, max = 239.93). Therefore, compensation based on median time to completion was $12.81/hr.

Demographics

Table 6 has the demographic results of Experiment 2. The average age of participants was 39, 55% were male, most were Caucasian (76%), and the majority were employed outside of
MTurk (79.5%). Most participants had some form of health insurance (81.8%), and over half avoided/delayed a medical procedure due to cost (56.2%).

<table>
<thead>
<tr>
<th>Table 6. Experiment 2 Demographics</th>
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<tbody>
<tr>
<td></td>
</tr>
<tr>
<td><strong>n/mean</strong></td>
</tr>
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<td>Age</td>
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<td>Lost Employment</td>
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<td>2-Medium</td>
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<td>Uninsured</td>
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<td>Either Avoided or Delayed</td>
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<tr>
<td>Underlying Conditions</td>
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<td>Trust in Doctors</td>
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</table>

*Note. For discrete variables, the number of participants and percentage of sample are*
included. For continuous variables, mean and SD are included. SF-12 maximum scores are 20 and 27 for PCS (Physical Component Summary) and MCS (Multiple Component Summary) respectively. Trust in doctors maximum score is 25. Both lost employment and healthcare refer to losing either due to the COVID-19 pandemic. SES strata were determined by combining income and education into a composite score based on Sheffer et al. (2017).

**Health Decision-Making**

Table 7 is a table of Spearman correlations for all behavioral measures for Experiment 2. Generally, health decision-making was strongly correlated. That is, those that were more likely to seek a medical professional for one symptom were likely to seek a medical professional for another. This pattern was consistent for severities across symptom as well. While decision-making for health was most correlated within a symptom rather than between, the as severity increased within a symptom, the association with other severities of that symptom decreased. Decision-making based on costs were also correlated, where similar costs for accessing healthcare were more correlated than for different costs. For medical decision-making, severity, \( \chi^2(1) = 722.36, p < .0001 \), symptom, \( \chi^2(2) = 87.79, p < .0001 \), and cost, \( \chi^2(2) = 1099.65, p < .0001 \), significant factors. There was a significant interaction between severity and cost, \( \chi^2(2) = 10.38, p = .0056 \), and between symptom and cost, \( \chi^2(4) = 10.99, p = .0267 \). There was no significant interaction between severity and symptom, \( \chi^2(2) = 2.25, p = .3239 \), or all three factors, \( \chi^2(4) = 1.83, p = .7667 \). As symptom severity increased, likelihood of seeking a medical professional increased, while seeking treatment for coughing was lowest, followed by headache, and finally nausea. As cost increased, seeking a medical professional decreased. Figure 7 shows a box plot of AUCord values by symptom, severity, and cost. Figure 8 shows interaction plots for symptom by cost, severity by cost, severity by symptom, and symptom by severity.
Table 7. Correlation Matrix of Behavioral Measures Based on AUC_{ords} from Experiment 2

<table>
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<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
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<td>0.28*</td>
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</tr>
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<td>0.49**</td>
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<td>0.33**</td>
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<td>0.65**</td>
<td>0.58**</td>
<td>0.76**</td>
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</tr>
</tbody>
</table>

Note. Spearman rank correlations between all monetary and health decision-making from Experiment 3. Mi: Mild severity. Se: Severe severity. H: Headache. C: Cough. N: Nausea. 10: $10 cost for accessing healthcare. 100: $100 cost for accessing healthcare. 1k: $1,000 cost for accessing healthcare. *: p < .05. **: p < .01. Values above the diagonal are corrected from multiple comparisons using the Holm-Bonferroni method.
Figure 7. Boxplot of Experiment 2 Medical Decision-Making

Note. Boxplots of AUC_{ord} of health decision-making questions in Experiment 2. Boxes represent the middle 50% of the distribution, white squares represent the mean, horizontal black lines represent the median. Whiskers are 1.5 x IQR. Symptoms are ordered by cough, headache, and nausea. Dotted line separates mild (left) from severe (right) symptoms. Higher AUC_{ord} indicate higher likelihood of seeking healthcare. Symptom, severity, and cost were all significant factors. There were significant interactions between cost and symptom and cost and severity.
Figure 8. Experiment 2 Interaction Plots

Note. Interaction plots for Experiment 2 health decision-making. Y-axes are mean AUC<sub>ord</sub>. Top left panel shows the interaction between symptom and cost of accessing healthcare, top right showing the interaction between severity and cost of accessing healthcare.

Model selection for health decision-making can be found in Table 8. The Rachlin model was generally favored (43.9% of all medical decision-making), with the GM model and noise models as 18.6% and 16.9% of probable models for medical decision-making respectively.
Table 8. Experiment 2 Model Selection Results

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<tr>
<th>Variable</th>
<th>Noise</th>
<th>Exponential</th>
<th>Hyperbolic</th>
<th>Green-Myerson</th>
<th>Rachlin</th>
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<td>9.6(14)</td>
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<td>44.5(65)</td>
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<td>Se H 10</td>
<td>14.4(21)</td>
<td>8.9(13)</td>
<td>11.6(17)</td>
<td>12.3(18)</td>
<td>52.7(77)</td>
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<td>8.9(13)</td>
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<td>17.1(25)</td>
<td>34.9(51)</td>
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<tr>
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<td>11.6(304)</td>
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</table>


JB criteria failures were generally low for bounce (4.1–8.2%), although higher for sensitivity (13.0–38.4%). There were 4.7% of data paths that failed both bounce and sensitivity criteria in Experiment 2. Table 9 contains the result of the JB criteria assessments for Experiment 2. As cost increased, JB failures of sensitivity also increased. Figures 9, 10, and 11 are line graphs of median health decision-making for cough, headaches, and nausea respectively.
### Table 9. Experiment 2 Johnson & Bickel Criteria

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<td>Mi C 1k</td>
<td>6.2(9)</td>
<td>30.8(45)</td>
<td>4.1(6)</td>
</tr>
<tr>
<td>Se C 1k</td>
<td>5.5(8)</td>
<td>14.4(21)</td>
<td>4.8(7)</td>
</tr>
<tr>
<td>Total</td>
<td>5.8(151)</td>
<td>18.4(483)</td>
<td>4.7(123)</td>
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</tbody>
</table>

Figure 9. Line Graphs of Experiment 2 Medical Decision-Making – Cough

Note. Line graph of median medical decision-making for cough in Experiment 2. Y-axis is the median likelihood of seeking a medical professional. X-axis is duration the symptom has persisted in days. Left panel shows the effect of cost to access healthcare for mild cough, whereas the right panel shows the effect of cost on severe cough.
Figure 10. Line Graphs of Experiment 2 Medical Decision-Making – Headaches

Note. Line graph of median medical decision-making for headaches in Experiment 2. Y-axis is the median likelihood of seeking a medical professional. X-axis is duration the symptom has persisted in days. Left panel shows the effect of cost to access healthcare for mild headaches, whereas the right panel shows the effect of cost on severe headaches.
Figure 11. Line Graphs of Experiment 2 Medical Decision-Making – Nausea

Note. Line graph of median medical decision-making for nausea in Experiment 2. Y-axis is the median likelihood of seeking a medical professional. X-axis is duration the symptom has persisted in days. Left panel shows the effect of cost to access healthcare for mild nausea, whereas the right panel shows the effect of cost on severe nausea.

Results of the aggregated MANOVAs from Experiment 2 can be found in Table 10. For coughing, age, $V = .22, F(6, 124) = 5.98, p < .0001$, SF-12 PCS, $V = .16, F(6, 124) = 4.06, p < .0001$, and avoided/delayed healthcare due to cost, $V = .12, F(6, 124) = 2.82, p = .0132$, were significant factors. For headaches, age, $V = .21, F(6, 124) = 5.33, p < .0001$, SF-12 PCS, $V = .17, F(6, 124) = 4.11, p = .0009$, and avoided/delayed healthcare due to cost, $V = .16, F(6, 124) =$
3.85, \( p = .0015 \), were significant factors. Lastly, SF-12 PCS, \( V = .22, F(6,124) = 5.72, p < .0001 \), having an underlying condition, \( V = .11, F(6, 124) = 2.64, p = .0193 \), and having avoided/delayed healthcare due to cost, \( V = .14, F(6, 124) = 3.44, p = .0036 \), were significant factors for nausea.

<table>
<thead>
<tr>
<th>Variable</th>
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<th>Nausea</th>
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<tr>
<td>Eth-Asian</td>
<td>0.0221</td>
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<td>Eth-Hispanic/Latin</td>
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<td>Eth-Black/African</td>
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<td>Eth-Other</td>
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<td>0.0063</td>
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<td>-0.0322</td>
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<tr>
<td>Avoided/Delayed Healthcare</td>
<td>-0.0933</td>
<td>-0.089</td>
<td>-0.0894</td>
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</table>

**Note.** Averaged parameter estimates from all linear regressions used in the MANOVA. **Bold:** Overall factors that were identified as significant from the MANOVA, not individual estimates. DD: Delay discounting. PD: Probability discounting. Cough, Headache, Nausea: Overall medical decision-making for respective symptom. Reference points for SES, gender, and ethnicity are SES-1, female, and Caucasian respectively. SF-12 PCS: Physical Component Summary scores. SF-12 MCS: Mental Component Summary Scores.

**Discussion**

Health decision-making was affected by cost and severity in expected ways. These results were similar to Experiment 1, in that increased symptom severity increased seeking a healthcare professional. Increased cost of healthcare decreased seeking a healthcare professional. Within
costs and symptoms, decision-making was correlated. In this sample, age was related to
treatment seeking for cough and nausea, whereas there was an inverse relationship between
physical health and treatment seeking for all symptoms. Having reported avoiding or delaying
seeing a doctor due to cost decreased likelihood of seeking treatment.

**Experiment 3**

**Methods**

The third experiment combined the first and second experiments such that delay and
probability discounting, framing (i.e., gaining money or losing money), symptom, severity, and
cost of healthcare utilization were assessed. Monetary discounting was assessed in the same way
as Experiment 1, but only the smaller monetary magnitudes were used ($500 and $1,000). This
reduced the number of monetary discounting questions from 40 to 20. All three symptoms were
used, but only mild and severe severities and costs of $10 and $1,000 were assessed. Order of
symptoms was randomly presented, but severities and costs were always in ascending order
much like in Experiment 2. Therefore, there were 60 health discounting questions, for a total for
80 discounting questions in Experiment 3.

**Results**

*Survey Duration and Screening*

Following screening there were data from 158 participants that were deemed as being
usable (78.0%). Median time to survey completion was 17.85 minutes (min = 5.90, max =
210.97). Therefore, compensation based on median time to completion was $11.76/hr.
Demographics

The demographic results of Experiment 3 are in Table 11. Most participants identified as being Caucasian (79.5%), male (60.9%), and having work outside of MTurk (75.6%). Mean age was 37.3, and nearly all participants had some form of health insurance coverage (92.3%).

Table 11. Experiment 3 Demographics

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<th>n/mean</th>
<th>%/SD</th>
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<td>3-High</td>
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</table>

Underlying Conditions
Trust in Doctors

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</thead>
<tbody>
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</tr>
</tbody>
</table>

*Note.* For discrete variables, the number of participants and percentage of sample are included. For continuous variables, mean and SD are included. SF-12 maximum scores are 20 and 27 for PCS (Physical Component Summary) and MCS (Multiple Component Summary) respectively. Trust in doctors maximum score is 25. Both lost employment and healthcare refer to losing either due to the COVID-19 pandemic. SES strata were determined by combining income and education into a composite score based on Sheffer et al. (2017).

**Monetary Discounting**

Table 12 is correlation matrix of Spearman correlations of all behavioral outcomes (i.e., monetary discounting and health decision-making) calculated by AUC<sub>ord</sub> in Experiment 3. Delay discounting measures were generally strongly correlated with each other, while not strongly correlated with probability discounting measures. Probability discounting of gains and losses were not correlated in this sample. There were some small correlations between delay discounting of gains and probability discounting of gains, but after corrections for multiple comparisons there were no significant associations between probability and delay discounting.
### Table 12. Correlation Matrix of Behavioral Measures Based on AUC_{ord}s from Experiment 3

<table>
<thead>
<tr>
<th>Variable</th>
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<th>2</th>
<th>3</th>
<th>4</th>
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<th>6</th>
<th>7</th>
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<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
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</thead>
<tbody>
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<td>0.1</td>
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<td>0.05</td>
<td>-0.24</td>
<td>-0.17</td>
<td>-0.22</td>
<td>-0.11</td>
<td>-0.27*</td>
<td>-0.27*</td>
<td>-0.05</td>
<td>0.05</td>
<td>-0.23</td>
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<tr>
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<td>0.53**</td>
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<td>-0.15</td>
<td>-0.01</td>
<td>-0.32**</td>
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<td>-0.34**</td>
<td>-0.34**</td>
<td>-0.04</td>
<td>0.05</td>
<td>-0.24</td>
<td>-0.17</td>
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</tr>
<tr>
<td>3. PD S +</td>
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<td>-0.11</td>
<td>0.01</td>
<td>-0.03</td>
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<td>0.07</td>
<td>0.15</td>
<td>0.05</td>
<td>0.18</td>
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<td>-0.03</td>
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</tr>
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<td>4. PD S -</td>
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<td>0.01</td>
<td>0.05</td>
<td>0.63**</td>
<td>0.52**</td>
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<td>0.44**</td>
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<td>0.28*</td>
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<tr>
<td>7. Mi H 10</td>
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<td>0.41**</td>
<td>0.77**</td>
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<td>0.42**</td>
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<tr>
<td>9. Mi C 10</td>
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<td>0.47**</td>
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<td>0.68**</td>
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<td>-0.05</td>
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<td>0.53**</td>
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<td>0.42**</td>
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<td>0.62**</td>
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<td>0.27**</td>
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<td>-0.05</td>
<td>-0.01</td>
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<td>0.28**</td>
<td>0.72**</td>
<td>0.39**</td>
<td>0.44**</td>
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<td>14. Se N 10</td>
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<td>0.05</td>
<td>-0.03</td>
<td>0.04</td>
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<td>0.45**</td>
<td>0.03</td>
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<td>0.18</td>
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<td>-0.24**</td>
<td>0.06</td>
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<td>0.19*</td>
<td>0.76**</td>
<td>0.7**</td>
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<td>0.37**</td>
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For delay discounting, there was a significant difference for the loss frame, $\chi^2(1) = 31.23$ $p < .0001$. Loss decreased discounting for delayed outcomes. For probability discounting, the loss frame was significant, $\chi^2(1) = 74.45, p < .0001$. Much like for delay discounting, the loss frame increased $\text{AUC}_{\text{ord}}$ of probability discounting (i.e., decreased discounting). Figure 12 is a boxplot of $\text{AUC}_{\text{ord}}$ of monetary discounting for Experiment 3.

*Figure 12. Boxplot of Experiment 3 Monetary Discounting*

Note. Boxplots of $\text{AUC}_{\text{ord}}$ of delay and probability discounting for Experiment 3. Boxes represent the middle 50% of the distribution, white squares represent the mean, horizontal black lines represent the median. Whiskers are 1.5 x IQR. Order for both delay and probability are by gains followed by losses. Higher values of delay $\text{AUC}_{\text{ord}}$ indicate less impulsive decision-
making, whereas higher values of probability AUC$_{ord}$ indicate greater risky decision-making. Frame was a statistically significant factor for delay and probability discounting.

The results of Gilroy et al.’s (2017) model selection process for each condition in Experiment 3 can be found in Table 13. For monetary discounting, the Rachlin model was heavily favored over other models (34.6%–74.2% of data paths), with the noise model being the second most favored (16.4%–49.7%). For delay discounting, the loss frame resulted in higher proportion of noise models (i.e., straight lines). Figure 13 are line graphs of the median indifference points for monetary discounting for Experiment 3.

### Table 13. Experiment 3 Model Selection Results

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<tr>
<td>DD S +</td>
<td>24.5(39)</td>
<td>8.2(13)</td>
<td>7.5(12)</td>
<td>3.1(5)</td>
<td>56.6(90)</td>
</tr>
<tr>
<td>DD S -</td>
<td>49.7(79)</td>
<td>6.3(10)</td>
<td>4.4(7)</td>
<td>5(8)</td>
<td>34.6(55)</td>
</tr>
<tr>
<td>PD S +</td>
<td>16.4(26)</td>
<td>6.3(10)</td>
<td>1.9(3)</td>
<td>1.3(2)</td>
<td>74.2(118)</td>
</tr>
<tr>
<td>PD S -</td>
<td>23.9(38)</td>
<td>5.7(9)</td>
<td>2.5(4)</td>
<td>1.9(3)</td>
<td>66(105)</td>
</tr>
<tr>
<td>Mi H 10</td>
<td>20.8(33)</td>
<td>11.9(19)</td>
<td>8.2(13)</td>
<td>5(8)</td>
<td>54.1(86)</td>
</tr>
<tr>
<td>Se H 10</td>
<td>31.4(50)</td>
<td>8.2(13)</td>
<td>9.4(15)</td>
<td>6.3(10)</td>
<td>44.7(71)</td>
</tr>
<tr>
<td>Mi H 1k</td>
<td>28.3(45)</td>
<td>8.8(14)</td>
<td>8.8(14)</td>
<td>15.1(24)</td>
<td>39(62)</td>
</tr>
<tr>
<td>Se H 1k</td>
<td>20.8(33)</td>
<td>6.9(11)</td>
<td>12.6(20)</td>
<td>14.5(23)</td>
<td>45.3(72)</td>
</tr>
<tr>
<td>Mi C 10</td>
<td>21.4(34)</td>
<td>11.3(18)</td>
<td>9.4(15)</td>
<td>6.3(10)</td>
<td>51.6(82)</td>
</tr>
<tr>
<td>Se C 10</td>
<td>22.6(36)</td>
<td>10.1(16)</td>
<td>5.7(9)</td>
<td>7.5(12)</td>
<td>54.1(86)</td>
</tr>
<tr>
<td>Mi C 1k</td>
<td>32.1(51)</td>
<td>6.3(10)</td>
<td>9.4(15)</td>
<td>11.9(19)</td>
<td>40.3(64)</td>
</tr>
<tr>
<td>Se C 1k</td>
<td>20.1(32)</td>
<td>9.4(15)</td>
<td>7.5(12)</td>
<td>20.1(32)</td>
<td>42.8(68)</td>
</tr>
<tr>
<td>Mi N 10</td>
<td>25.8(41)</td>
<td>8.8(14)</td>
<td>6.9(11)</td>
<td>10.1(16)</td>
<td>48.4(77)</td>
</tr>
<tr>
<td>Se N 10</td>
<td>23.9(38)</td>
<td>8.2(13)</td>
<td>9.4(15)</td>
<td>10.1(16)</td>
<td>48.4(77)</td>
</tr>
<tr>
<td>Mi N 1k</td>
<td>26.4(42)</td>
<td>6.9(11)</td>
<td>11.3(18)</td>
<td>19.5(31)</td>
<td>35.8(57)</td>
</tr>
<tr>
<td>Se N 1k</td>
<td>19.5(31)</td>
<td>8.2(13)</td>
<td>6.9(11)</td>
<td>22.6(36)</td>
<td>42.8(68)</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>25.5(648)</td>
<td>8.2(209)</td>
<td>7.6(194)</td>
<td>10(255)</td>
<td>48.7(1238)</td>
</tr>
</tbody>
</table>

Figure 13. Line Graphs of Experiment 3 Monetary Discounting

*Note.* Line graphs of delay (left panel) and probability (right panel) discounting in Experiment 3. Y-axis represents the likelihood a participant would choose the ‘better option’ (i.e., larger reward or smaller loss) for delay and probability discounting. Delays are in days and probabilities are in percent chance of larger reward. Note that percent chance is in descending rather than ascending order to allow for comparisons with delay discounting.

The JB assessment of discounting can be found in Table 14 based on condition. Some data paths for monetary discounting were identified as having bounce (6.9% – 16.4%), while more were identified as not meeting the sensitivity criteria (17.0%–51.6%). Much like in Experiment 1, the loss frame had the highest failures of sensitivity. Generally, there was a low percentage of data paths that failed both JB criteria (5.0%–11.9%) for monetary discounting.
Table 14. Experiment 3 Johnson & Bickel Criteria

<table>
<thead>
<tr>
<th>Variable</th>
<th>Bounce % Failures</th>
<th>Sensitivity % Failures</th>
<th>Both % Failures</th>
</tr>
</thead>
<tbody>
<tr>
<td>DD S +</td>
<td>6.9(11)</td>
<td>25.2(40)</td>
<td>5(8)</td>
</tr>
<tr>
<td>DD S -</td>
<td>8.8(14)</td>
<td>51.6(82)</td>
<td>7.5(12)</td>
</tr>
<tr>
<td>PD S +</td>
<td>7.5(12)</td>
<td>17(27)</td>
<td>6.9(11)</td>
</tr>
<tr>
<td>PD S -</td>
<td>16.4(26)</td>
<td>21.4(34)</td>
<td>11.9(19)</td>
</tr>
<tr>
<td>Mi H 10</td>
<td>13.2(21)</td>
<td>22(35)</td>
<td>11.9(19)</td>
</tr>
<tr>
<td>Se H 10</td>
<td>11.3(18)</td>
<td>30.2(48)</td>
<td>10.7(17)</td>
</tr>
<tr>
<td>Mi H 1k</td>
<td>10.7(17)</td>
<td>29.6(47)</td>
<td>6.3(10)</td>
</tr>
<tr>
<td>Se H 1k</td>
<td>8.2(13)</td>
<td>22(35)</td>
<td>6.9(11)</td>
</tr>
<tr>
<td>Mi C 10</td>
<td>10.7(17)</td>
<td>21.4(34)</td>
<td>6.9(11)</td>
</tr>
<tr>
<td>Se C 10</td>
<td>11.9(19)</td>
<td>22.6(36)</td>
<td>10.1(16)</td>
</tr>
<tr>
<td>Mi C 1k</td>
<td>9.4(15)</td>
<td>35.8(57)</td>
<td>8.8(14)</td>
</tr>
<tr>
<td>Se C 1k</td>
<td>8.8(14)</td>
<td>20.1(32)</td>
<td>6.9(11)</td>
</tr>
<tr>
<td>Mi N 10</td>
<td>11.9(19)</td>
<td>24.5(39)</td>
<td>10.7(17)</td>
</tr>
<tr>
<td>Se N 10</td>
<td>8.2(13)</td>
<td>22(35)</td>
<td>6.9(11)</td>
</tr>
<tr>
<td>Mi N 1k</td>
<td>7.5(12)</td>
<td>28.3(45)</td>
<td>5(8)</td>
</tr>
<tr>
<td>Se N 1k</td>
<td>9.4(15)</td>
<td>22(35)</td>
<td>8.8(14)</td>
</tr>
<tr>
<td>Total</td>
<td>10.1(256)</td>
<td>26(661)</td>
<td>8.2(209)</td>
</tr>
</tbody>
</table>


For delay discounting, only the SF-12 PCS was a significant factor, $V = .12$, $F(2, 138) = 9.24$, $p = .0002$. There were no significant demographic factors for probability discounting. Table 15 has the aggregated estimated for monetary discounting and health decision-making.

Table 15. Experiment 3 Aggregated Relationships with Demographics

<table>
<thead>
<tr>
<th>Variable</th>
<th>DD</th>
<th>PD</th>
<th>Cough</th>
<th>Headache</th>
<th>Nausea</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>0.0028</td>
<td>-0.0012</td>
<td>-0.0011</td>
<td>-0.0019</td>
<td>0.0006</td>
</tr>
<tr>
<td>SES-2</td>
<td>0.001</td>
<td>-0.076</td>
<td>0.2841</td>
<td>0.2153</td>
<td>0.2179</td>
</tr>
<tr>
<td>SES-3</td>
<td>-0.028</td>
<td>-0.098</td>
<td>0.3309</td>
<td>0.2334</td>
<td>0.273</td>
</tr>
<tr>
<td>Gen-Male</td>
<td>0.0256</td>
<td>0.0312</td>
<td>0.0311</td>
<td>-0.0139</td>
<td>-0.04</td>
</tr>
<tr>
<td>Gen-Other</td>
<td>-0.2146</td>
<td>-0.3357</td>
<td>-0.0275</td>
<td>0.123</td>
<td>0.2231</td>
</tr>
<tr>
<td>Eth-Asian</td>
<td>0.1839</td>
<td>0.024</td>
<td>0.0825</td>
<td>0.0295</td>
<td>0.0163</td>
</tr>
<tr>
<td>Eth-Hispanic/Latin</td>
<td>-0.0091</td>
<td>0.0363</td>
<td>0.0846</td>
<td>0.0736</td>
<td>0.0579</td>
</tr>
<tr>
<td>Eth-Black/African</td>
<td>-0.1718</td>
<td>0.007</td>
<td>0.0821</td>
<td>0.0285</td>
<td>0.0893</td>
</tr>
</tbody>
</table>

75
Table 12 is a table of Spearman correlations for all behavioral measures for Experiment 3. Generally, health decision-making was correlated. That is, those that were more likely to seek a medical professional for one symptom were likely to seek a medical professional for another. This pattern was consistent for severities across symptom as well. While decision-making for health was most correlated within a symptom rather than between, the as severity increased within a symptom, the association with other severities of that symptom decreased. This pattern was also true for cost, much like in Experiment 2. For medical decision-making, severity, $\chi^2(1) = 259.78, p < .0001$, and symptom, $\chi^2(2) = 30.16, p < .0001$, and cost, $\chi^2(1) = 550.36, p < .0001$, were significant factors. There was no significant interaction between the any combination or all three of the factors. As symptom severity increased, likelihood of seeking a medical professional increased, while seeking treatment for coughing was lowest, followed by headache, and finally nausea. Figure 14 is a boxplot of AUCord for health decision-making in Experiment 3.
Figure 14. Boxplot of Experiment 3 Medical Decision-Making

Note. Boxplots of AUC_{ord} of health decision-making questions in Experiment 3. Boxes represent the middle 50% of the distribution, white squares represent the mean, horizontal black lines represent the median. Whiskers are 1.5 x IQR. Symptoms are ordered by cough, headache, and nausea. Dotted line separates mild (left) from severe (right) symptoms. Severity, cost, and symptom were all statistically significant factors. There was no significant interaction between an factors.

Model selection for health decision-making can be found in Table 13. The Rachlin model was favored in most cases (35.8%–54.1%) followed by the noise model (6.3%–32.1%), with fairly similar proportions between the other models. JB criteria failures were slightly higher than the other two experiments (7.5%–13.2%), sensitivity (20.1%–35.8%), and both (5.0%–11.9%).
As severity increased, JB failures of sensitivity also increased. Results of the JB criteria can be found in Table 14. Figures 15, 16, and 17 are line graphs of median indifference points for health decision-making for cough, headache, and nausea respectively.

Figure 15. Line Graphs of Experiment 3 Medical Decision-Making – Cough

Note. Line graph of median medical decision-making for cough in Experiment 3. Y-axis is the median likelihood of seeking a medical professional. X-axis is duration the symptom has persisted in days. Left panel shows the effect of cost to access healthcare for mild cough, whereas the right panel shows the effect of cost on severe cough.
Figure 16. Line Graphs of Experiment 3 Medical Decision-Making – Headaches

Note. Line graph of median medical decision-making for headaches in Experiment 3. Y-axis is the median likelihood of seeking a medical professional. X-axis is duration the symptom has persisted in days. Left panel shows the effect of cost to access healthcare for mild headaches, whereas the right panel shows the effect of cost on severe headaches.
Figure 17. Line Graphs of Experiment 3 Medical Decision-Making – Nausea

Note. Line graph of median medical decision-making for nausea in Experiment 3. Y-axis is the median likelihood of seeking a medical professional. X-axis is duration the symptom has persisted in days. Left panel shows the effect of cost to access healthcare for mild nausea, whereas the right panel shows the effect of cost on severe nausea.

Delay discounting for gains and losses was significantly related to most health decision-making scenarios, with an inverse relationship between seeking health treatment and monetary discounting. That is, those who might be considered as “more impulsive” based on monetary discounting were more likely to seek treatment earlier than those who were “less impulsive” based on monetary discounting. Riskiness (i.e., probability discounting) did not seem to be
related to health decision-making. These are the same pattern of results from Experiment 1 with regard to the relationship between monetary discounting and health decision-making. Generally, delay discounting of losses was more associated with medical decision-making. Also like in Experiment 1, delay discounting was less associated with nausea than other symptoms.

For cough, the SF-12 PCS, $V = .16$, $F(4, 136) = 6.62, p < .0001$, and having avoided/delayed healthcare due to cost, $V = .13$, $F(4, 136) = 5.21, p = .0006$, were significant factors. For headaches, SF-12 PCS, $V = .08$, $F(4, 136) = 2.85, p = .0264$, and avoided/delayed healthcare due to cost, $V = .11$, $F(4, 136) = 4.06, p = .0038$, were significant factors. Lastly, age, $V = .07$, $F(4, 136) = 2.73, p = .0315$, SF-12 PCS, $V = 0.16$, $F(4, 136) = 6.71, p < .0001$, and having avoided/delayed healthcare due to cost, $V = .13$, $F(4, 136) = 5, p = .0009$, were significant factors for nausea. Table 15 contains the aggregated estimates of linear regressions from Experiment 3.

**Discussion**

Results of Experiment 3 were similar to those of Experiments 1 and 2. Monetary discounting displayed the expected effects of gain and loss, while delay and probability were not related to each other. Health decision-making followed the same pattern as Experiment 2, with cost suppressing seeking a medical professional and severity increasing seeking a medical professional. For relationships with demographic variables, physical health had an inverse relationship with seeking a healthcare professional and previously avoiding/delaying seeing a doctor due to cost decreased medical decision-making. These are similar to the results of Experiment 2.
Predicting Healthcare Seeking

Because the Rachlin model was favored most often against other models, it was used to
determine the effective duration of symptoms for when someone is at least 50% likely to seek
healthcare (EDur50). This was accomplished used the nls package in R and using the formula
\((1/k)^{1/s}\) proposed by Franck et al. (2015) to calculate ED50 derived from the Rachlin model.
EDur50 can be interpreted as the number of days a symptom has been occurring based on
associated severity and cost before an individual is likely to seek healthcare for that experienced
symptom. EDur50 was calculated on the median data from each health decision-making scenario
across all three experiments as a proof of concept. Table 16 contains the EDur50 based on
median values from all experiments.

<table>
<thead>
<tr>
<th>Experiment/Severity/Cost</th>
<th>Symptom</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Headache</td>
<td>Cough</td>
</tr>
<tr>
<td>Experiment 1 Mild</td>
<td>9.52</td>
<td>14.46</td>
</tr>
<tr>
<td>Moderate</td>
<td>5.40</td>
<td>7.49</td>
</tr>
<tr>
<td>Severe</td>
<td>1.76</td>
<td>2.12</td>
</tr>
<tr>
<td>Mild $10</td>
<td>6.50</td>
<td>10.94</td>
</tr>
<tr>
<td>Mild $100</td>
<td>19.92</td>
<td>37.80</td>
</tr>
<tr>
<td>Mild $1,000</td>
<td>145.45</td>
<td>240.78</td>
</tr>
<tr>
<td>Severe $10</td>
<td>1.08</td>
<td>1.72</td>
</tr>
<tr>
<td>Severe $100</td>
<td>4.08</td>
<td>5.76</td>
</tr>
<tr>
<td>Severe $1,000</td>
<td>16.29</td>
<td>31.39</td>
</tr>
<tr>
<td>Experiment 2 Mild $10</td>
<td>4.06</td>
<td>7.56</td>
</tr>
<tr>
<td>Mild $1,000</td>
<td>53.82</td>
<td>73.22</td>
</tr>
<tr>
<td>Severe $10</td>
<td>0.86</td>
<td>1.63</td>
</tr>
<tr>
<td>Severe $1,000</td>
<td>8.80</td>
<td>14.01</td>
</tr>
</tbody>
</table>

Note. Effective duration of symptoms experienced before likely seeking
treatment (EDur50) based on median based on the Rachlin model for all
conditions. EDur50 was derived used \((1/k)^{1/s}\). EDur50 can be interpreted as the
day where treatment seeking becomes above 50% likely. Higher values of
EDur50 indicate delaying treatment seeking longer.
Values of EDur50 were lowest (i.e., healthcare sought sooner) for severe symptoms and low costs. By contrast, costs increased higher delays in seeking healthcare by up to 22 times (e.g., cough in Experiment 2). Figure 18 is a visualization of EDur50 values across experiments.

*Figure 18. Plot of EDur50 Values from all Experiments*

*Note.* Plot of effective duration of symptoms experienced before 50% of seeking healthcare (EDur50). X-axis is the log-scaled duration of a symptom in days. White: Mild symptoms, Grey: Moderate Symptoms, Black: Severe symptoms. Circles are headaches, diamonds are cough, and triangles are nausea. Values to the left indicate seeking treatment sooner, whereas values to the right indicate delaying treatment. Y-axis for Experiment 2 and 3 indicate cost of seeking healthcare.
Correlates of Preventive Health Behaviors

Based on the SF-12 PCS scores being positively related to delay discounting and inversely related to seeking healthcare, exploratory analyses were conducted on the preventive health measure (flossing) included in the demographic questions. Frequency of flossing was compared with monetary discounting by combining the results of common monetary discounting questions from Experiments 1 and 3. This resulted in a total of 324 participants’ data to identify if there was a relationship between small delay and probability discounting scenarios and how often participants floss. The purpose of assessing this relationship was to identify if there might be an association between preventive behaviors (e.g., flossing) and measures of impulsivity or riskiness. Figure 18 is a series of boxplots of $\text{AUC}_{\text{ord}}$ values plotted against frequency of flossing. There were 110 participants who identified as flossing daily, 86 flossing weekly, 38 monthly, 35 biannually, 28 annually, and 29 flossing less than annually.
Figure 19. Boxplots of Flossing and Monetary Discounting from Experiments 1 and 3

Note. Boxplots of AUC$_{ord}$ for small delayed gains (top left), small delayed losses (bottom left), small probabilistic gains (top right), and small probabilistic losses (bottom right). Boxes represent the middle 50% of the distribution, white squares represent the mean, horizontal black lines represent the median. Whiskers are 1.5 x IQR. Frequency of flossing is Da: at least daily, We: at least weekly, Mo: at least monthly, BiAn: at least biannually, An: at least annually, < An: Less than annually. *: Lower significant differences from flossing daily. ~: Higher significant difference from daily flossing. Higher values of delay AUC$_{ord}$ indicate less impulsive decision-making, whereas higher values of probability AUC$_{ord}$ indicate greater risky decision-making.
Delay and probability discounting were significantly related to frequency of flossing, although visually flossing had a clearer relationship to delay discounting, with those who flossed daily having lower impulsivity scores as determined by measures of delay discounting.

Because the SF-12 PCS scores were identified as significant in most of the MANOVAs across experiments for delay discounting and medical decision-making, PCS scores from all 467 participants were also plotted against frequency of flossing. MCS scores were also compared to flossing for posterity. Boxplots of SF-12 PCS and MCS scores and flossing can be found in Figure 19. For all experiments combined, there were 160 participants who identified as flossing daily, 126 flossing weekly, 59 monthly, 48 biannually, 36 annually, and 38 flossing less than annually.
Figure 20. Boxplot of SF-12 PCS Scores and Flossing from all Experiments

**Note.** Boxplots of SF-12 PCS (left) and SF-12 MCS (right) scores from all experiments combined plotted against flossing frequency. Boxes represent the middle 50% of the distribution, white squares represent the mean, horizontal black lines represent the median. Whiskers are 1.5 x IQR. Frequency of flossing is Da: at least daily, We: at least weekly, Mo: at least monthly, BiAn: at least biannually, An: at least annually, < An: Less than annually. *: Lower significant difference from flossing daily. Higher values indicate higher physical health. The maximum scores for the PCS and MCS are 20 and 27 respectively.

Much like delay discounting, PCS scores followed a similar pattern with frequency of flossing, where those who were more likely to floss were also more likely to have better physical health.

MCS scores also followed the same pattern, even though they were not identified as significant via MANOVAs from Experiment 1 or 3. Because of this, correlations between measures and monetary discounting were assessed using Spearman rank correlations which are available in Table 17.
### Table 17. Relationship Between SF-12 Summary Scores and Monetary Discounting from Experiments 1 and 3

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. DD S +</td>
<td>0.53**</td>
<td>0.16*</td>
<td>0.11</td>
<td>0.25**</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>2. DD S -</td>
<td>0.53**</td>
<td>0</td>
<td>0.18*</td>
<td>0.27**</td>
<td>0.09</td>
<td></td>
</tr>
<tr>
<td>3. PD S +</td>
<td>0.16**</td>
<td>0</td>
<td>-0.14</td>
<td>-0.02</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>4. PD S -</td>
<td>0.11</td>
<td>0.18**</td>
<td>-0.14*</td>
<td>0.04</td>
<td>-0.01</td>
<td></td>
</tr>
<tr>
<td>5. PCS</td>
<td>0.25**</td>
<td>0.27**</td>
<td>-0.02</td>
<td>0.04</td>
<td>0.59**</td>
<td></td>
</tr>
<tr>
<td>6. MCS</td>
<td>0</td>
<td>0.09</td>
<td>0</td>
<td>-0.01</td>
<td>0.59**</td>
<td></td>
</tr>
</tbody>
</table>

*Note.* Spearman rank correlations between all monetary discounting and SF-12 scores from Experiments 1 and 3. DD: Delay Discounting. PD: Probability Discounting. S: Small Magnitude. +: Gain frame. -: Loss frame. PCS: SF-12 Physical Component Summary Score. MCS: SF-12 Mental Component Summary Score. Dashed lines separate monetary discounting and SF-12 scores. *: $p < .05$. **: $p < .01$. Values above the diagonal are corrected from multiple comparisons using the Holm-Bonferroni method.

While the relationship between flossing and MCS scores appeared to follow the same pattern as delay discounting and PCS scores, the correlation analysis indicated that there was no relationship between MCS and discounting. Even though scores on the MCS and PCS were strongly correlated, only the PCS was related to delay discounting. In no case was probability discounting related to physical or mental health measures. This post-hoc analysis adds credibility to the positive relationship between physical health, delay discounting, and preventive health behaviors.

**General Discussion**

Seeking healthcare systematically increased with severity of symptoms, and different symptoms resulted in differential treatment seeking. Physical health, having previously avoided/delayed healthcare due to cost, delay discounting, and flossing were all related to seeking healthcare, where those that with better health displayed less impulsivity, but also were more likely to engage in a preventive health behavior (i.e., flossing). The proof of concept measure of EDur50 was also successfully employed to predict the duration a symptom at a given severity and cost needed to be experienced prior to when one might to seek healthcare. Also, as
the cost of accessing healthcare increased, the likelihood of seeking healthcare decreased (i.e., duration of symptoms experienced prior so seeking healthcare increased). This adds to the body of evidence that cost is a meaningful factor for an individual’s determination to seek professional healthcare.

**Health Decision-Making**

Health decision-making followed the pattern of hypothesized results. As the severity of a symptom increased, the likelihood of seeking medical help also increased. An inverse relationship was also found between cost of healthcare and treatment seeking. Treatment seeking was generally highly correlated within a given a symptom and was also more correlated across symptoms when the severity was the same. This same pattern also occurred for cost. Therefore, severity, cost, and symptom were all independent regarding how they govern medical decision-making. Those who are more likely to seek treatment at a given cost will do so regardless of symptom, and the same occurs for severity. However, cost overrode these factors, as indicated by how the association within and between symptom changed as a function of cost. There was also a commodity effect that occurred between symptoms. Cough was consistently the symptom the had the lowest likelihood of seeking medical help, followed by headaches, and lastly nausea with the highest likelihoods of seeking medical help across all experiments. This commodity effect is consistent with previous research (Sawicki & Markiewicz, 2016; Weatherly & Terrell, 2014), although the authors of those studies claimed to be assessing the magnitude effect. Given that the health conditions in those studies compared across qualitatively different health outcomes (i.e., acne and cancer, acne and paralysis) rather than within health outcomes, it is fair to identify the observed effects due to the commodity assessed (i.e., the qualitatively different outcome). This commodity effect has also been shown for preferences between different sequences of improving
or deteriorating health outcomes, such as wrinkles, acne, and headaches (Chapman, 2000). In the case of the current study, correlations for health decision-making were highest within a given symptom, which is similar to the results of Charlton and Fantino (2008) and Holt et al. (2016) in which commodities that were most similar had more similar discounting rates compared to commodities that were dissimilar.

Interestingly, probability discounting for money was not related to medical decision-making at all. Riskiness assessed via probability discounting was not a relevant factor for treatment seeking. However, delay discounting was generally correlated with medical decision-making for cough and headaches, but not nausea. Those who were more “impulsive” (i.e., lower AUCord) were more likely to seek treatment sooner than those who were less “impulsive”. This makes some intuitive sense, as those who are less likely to wait for a monetary outcome may also be less likely to wait for other outcomes or information. In this case, a participant who was a steep monetary discounter may be less willing to see if a symptom stops on its own rather than those who are shallower discounters. That this relationship did not occur with nausea provides further evidence that each symptom acts as a separable commodity. In this way it appears that not all health decisions are the same or might not all be related to a unified decision-making process (e.g., delay discounting). Another possibility is that there is an unmeasured moderating variable not identified in the present study and further investigation is required. In the present study, those who identified as having an underlying condition were less likely (although only significantly so in Experiment 2) to seek healthcare for nausea relative to other conditions. It may be that those who regularly experience a given symptom due to an underlying condition or disease modifying treatment may be less inclined to seek healthcare for those symptoms. That is, the individual has become habituated to nausea and it may not be evoke treatment seeking due to
the underlying cause of that symptom being known to the individual (e.g., chemotherapy causes nausea, if I am nauseous and on chemotherapy, I may not seek medical treatment because I know the nausea is due to chemotherapy). Lifetime experience with a symptom may be the moderating variable to help clarify the differential healthcare seeking between symptoms. The result that healthcare seeking was positively related to impulsivity is in contrast with meta-analytic results of Odum et al. (2020) that did find an inverse relationship between impulsivity and health scenarios (i.e., lower impulsivity was correlated with lower discounting of health outcomes). This will be discussed in more detail in the section covering methodological considerations.

Regarding associations between demographic characteristics and health decision-making, the only significant factors that were replicated across experiments were physical health identified via the SF-12 PCS and having previously avoided/delaying seeing a medical professional due to cost. Increased physical health decreased the likelihood of seeking treatment, while having previously avoiding/delaying medical help decreased the likelihood of seeking treatment. While this only occurred for Experiments 2 and 3, the effect of physical health was significant for cough and was non-significant for other symptoms in Experiment 1 although the direct of the effect remained the same. Interestingly, Experiments 2 and 3 were also the two experiments where health scenarios had an associated cost. In Experiment 1, there was a non-significant effect of an increase in seeking a medical professional for those that had delayed/avoided a medical professional due to cost which was the opposite to the other two experiments. The health scenarios in Experiment 1 did not have an associated cost, and this could be the primary reason as to why there was a difference between these experiments. Health questions involving cost may have evoked more relevant historical experiences during responding. These questions may have been more ecologically valid than those without
associated costs, as the sample was pulled from the United States. This may also be indicative of some form of contrast between having experienced real consequences due to cost and responding was influenced by there being a lack of cost for the health scenarios in Experiment 1. That is, not having delayed/avoided healthcare due to cost decreased the likelihood of treatment seeking for scenarios which involved cost, but increased treatment seeking when cost was not a factor. If this is the case, individuals from countries with socialized healthcare may respond differently when cost is associated with seeking treatment relative those familiar with privatized healthcare. For example, an American may already incorporate cost into medical decision-making, while a Canadian may not. Given that cost affects medical decision-making, those from countries who do not have upfront costs may be more sensitive (i.e., less likely to seek treatment) to cost increases to access healthcare. However, this needs to be explored further in future studies comparing samples of participants outside the US.

Prediction of group healthcare seeking was also accomplished through the use of EDur50. This was done using the most chosen model (i.e., Rachlin) and extracting the EDur50 from model estimates of median data of health decision-making. This allowed a straightforward interpretation of when one might seek healthcare for any given symptom, as well as an easy-to-interpret metric of how cost impacts healthcare seeking. For example, increasing the cost of accessing healthcare from $10 to $100 shifted the EDur50 ~3.4 times for mild symptoms and up to ~3.7 times for severe symptoms.

**Model Selection of Health Decisions**

For health decision-making, the Rachlin model was chosen most as the most probable model for all scenarios. The exponential model was typically the least selected probable model on average but was close to the hyperbolic model. The GM model was the most probable model
after the Rachlin model. The noise model was selected as the most probable for a sizeable amount of the data paths assessed. This could be due to the number of JB criteria failures which will be discussed in the next section, as the proportion of noise models as the most likely model corresponded with the number of data paths that failed the JB sensitivity criteria. Overall, these general results indicate that health decision-making scenarios like the ones in the present study produce data similar to traditional monetary discount and that health-relation decision-making for treatment seeking may follow similar patterns.

**Monetary Discounting**

The results of monetary discounting from Experiment 1 replicated previous research assessing framing or magnitude as values of $AUC_{ord}$ increased for loss frames and large monetary values for delay discounting (e.g., Baker et al., 2003; Furrebøe, 2020; MerKerchar et al., 2013). However, while the framing effect occurred for probability discounting in the expected direction, no magnitude effect occurred. This is somewhat unexpected, as a reverse magnitude effect has typically been found for probability discounting of gains (e.g., Du et al., 2002; Myerson et al., 2011; Weatherly & Terrell, 2014; Yi et al., 2006). Why this is the only effect that was not replicated is unclear. It is possible that the size of the magnitude difference was not large enough to evoke the effect, but at this time it is unclear for why this was the only effect not replicated. It could also be that probability discounting is a less explored phenomena than delay discounting, and there have been fewer opportunities for failures to replicate. For Experiment 3, the framing effect was replicated for both probability and delay discounting.

While there was no consistent demographic variable related to monetary discounting, an interesting note is that identifying as a smoker did slightly decrease $AUC_{ord}$ (i.e., increased discounting) for delay, but not probability, discounting. Delay discounting was generally
correlated with other delay discounting scenarios, but probability discounting was not correlated between magnitudes. Probability discounting was only correlated within gain/loss frames, but not across gain/loss frames like delay discounting was.

Overall, monetary discounting occurred exactly as expected with the exception of the reverse magnitude effect for probability discounting. Much like previous studies that compared discounting models, the Rachlin model was the most selected probable model for data paths, while the exponential model was the least selected model. The noise model generally corresponded with the number of data paths that failed the JB sensitivity criteria. Delay and probability discounting were not significantly correlated, indicating that delay and probability are governed by separate processes (e.g., Green & Myerson, 2013).

**Methodological Considerations**

For monetary discounting, JB criteria were generally within the expected number of non-systematic data paths based on Smith et al. (2018). It should be noted that Rung et al. (2018) compared fixed, titrating, and VAS versions of discounting tasks and identified that the VAS had an “unacceptable” (i.e., data paths that failed the either of the JB criteria) percentage of data paths (47.3%). However, delay discounting assessed by the likelihood VAS in the present study was lower for the small delay discounting gains (Experiment 1: 27.9%; Experiment 3: 32.1%). These numbers from the present study are similar to the fixed (29.6%) and titrating tasks (26.3%) used by Rung et al. (2018). Part of the reason for this difference may have been due to the equivalence form of VAS that Rung et al. used, where the slider indicated the equivalent value rather than the likelihood of choosing between two options. While there were some conditions with an increased number of data paths that failed the sensitivity criteria for monetary discounting, such as the larger magnitude and loss frames, there is a practical reason for this (i.e.,
ceiling effect). Based on the median data points and AUC$_{ord}$ for monetary discounting, most participants exclusively were choosing the “better” option at more delays, leading it to appear that participants were insensitive to the delay manipulations. This is most likely due to the delay values chosen rather than a lack of sensitivity. Contrasted with health decision-making, there were fewer data paths across all experiments that failed JB criteria for seeking medical help. The exceptions were for severe symptoms at no cost and mild symptoms at high costs (i.e., $1,000) which had an increased number of sensitivity failures. This is because of a ceiling/floor effect, where if a participant was to always seek healthcare at high symptom severity, or never seek healthcare due to high cost, it would appear as if though they were insensitive to the symptom duration manipulations. Conceptually, and given one of the hypotheses of this study, this makes perfect sense as cost was assumed to suppress decision-making either partially or entirely. Bounce criteria did not seem to be affected by these manipulations. Furthermore, using Experiment 1 as an example, JB sensitivity failures decreased for health decision-making (10.9–22.4%). Part of this could be due to the nature of these questions being more ecologically relevant compared to monetary discounting questions. That is, participants were probably more likely to have experienced making a medical decision such as what was presented, rather than the monetary decisions used in typical discounting research. Given that the total number of data paths that failed both bounce and sensitivity criteria was generally low (3.9%, 4.7%, and 8.2% for Experiments 1, 2, and 3 respectively), it seems that the VAS and type of questions asked were well within tolerance and that this version of the VAS for discounting-based decision-making tasks was appropriate.

This study also found results that were contrary to those in previous studies that found a positive relationship between discounting measures of monetary and health outcomes (e.g.,
Baker et al., 2003; Johnson et al., 2007; Friedel et al., 2016. The primary reason for this may be simply the way in which questions were asked. In the case of “health boost” scenarios, this is a rather abstract scenario that practically may never occur, and respondents to these scenarios may value, in the abstract sense, more delayed health later. This might correspond to other preventive behaviors that are typically associated with discounting measures (Story et al., 2014). This is because it could be assumed that those with better physical health may already engaging in measures to improve physical health which are antithetical to impulsive behavior, which is supported by the relationship between flossing, delay discounting, and the SF-12 PCS scores identified during the post-hoc analysis. However, causality of these relationships could not be determined. In the current study, health scenarios were directly related to a participant’s hypothetical and immediate situation. Questions were not framed as whether a participant wanted a small good thing now or a big good thing later, but instead how likely they were to act about in a hypothetical present situation. Assuming that delay discounting for monetary outcomes is an assessment of impulsivity, the format of questions in the current study may capture this “in-the-moment” decision-making whereas abstract or distant scenarios may capture something else. Which type of question is more relevant to actual outcomes is an empirical question to be explored in the future.

Limitations

A major limitation is that there are many aspects of the decision-making process not captured in the current study. While immediate symptoms are a factor in decision-making to seek professional help, numerous sources of free information regarding current symptoms are available via the internet. This aspect of the decision-making process was not captured, and interesting relationships with traditional monetary discounting measures may have been missed.
For example, if a question asked, how likely are you to seek medical help after seeing that your symptoms might be related to cancer, would probability discounting then be correlated with decision-making? That is, there is not a clear risk associated with a potential underlying condition versus simply the hypothetical symptom alone. Cost was also the only barrier to healthcare that was assessed. Other factors such as distance to clinics and wait times were not assessed but would be important to examine as they have previously been identified as negatively correlated with healthcare utilization (e.g., Buzza et al., 2011; Virgilsen et al., 2019). It may be that participants made this consideration, as “time is money” is a common adage. Whether cost, distance to healthcare, and healthcare wait times are separable is area that ought to be explored. Also missing is how people might try to mitigate symptoms prior to seeking healthcare, such as over-the-counter remedies and naturalistic remedies.

Another limitation of the current study was this it used hypothetical tasks to assess health decision-making without any comparisons to real health behavior. A future study could compare results of these types of health decision-making questions to actual medical reports for when individuals make contact with a health professional. Also, the current study consisted of participants from MTurk. While there are limitations of using this population there are also benefits to using them relative to typical undergraduate psychology students (Clifford et al., 2015; Merz et al., 2020). For example, demographics were generally more varied that what are found in undergraduate samples. Because the scenarios in this study assessed medical decision-making involving cost of accessing healthcare, having a population that is less likely to still be supported financially by their parents/guardians helps improve external validity of these results. For data analytic purposes, the demographics of the current samples were overwhelmingly Caucasian and there were few participants who were of the lowest SES category, making it
difficult to assess the relationship between those variables and responses to the hypothetical scenarios. Another limitation is that only flossing was assessed as a preventive health behavior. Determining how other behaviors such as healthy eating, regular exercise, or drug use may help to elucidate the relationship between preventive health behaviors and treatment seeking for current and immediate symptoms.

**It’s Still the Prices, Stupid**

The cost of healthcare in the US is an important factor that prevents many Americans from accessing necessary medical help. Results of the current study indicate that associating a cost with healthcare produces a reliable decrease in seeking medical help. More importantly, roughly half of participants reported having avoided or delayed a real medical appointment or procedure due to cost. Sweeping systemic change is required to produce better health outcomes in the United States, and the results of this study help to highlight the impact that cost of accessing healthcare has on utilization. If one of the goals of having a healthcare system is to help keep a population healthy, identifying and decreasing barriers to utilization should help achieve that goal. While qualitative data regarding the circumstances of delaying/avoiding were collected, they were not reported because the experiences provided by participants were unsurprising. Many participants reported missing routine or potential emergency health procedures due to cost. However, one particular response shared by a participant perfectly encapsulates the issues inherent in the American medical system and the urgency of why it needs to be fixed:

I am doing this right now. I have a subclavian aneurysm that’s grown to the size of a golf ball. It has to be surgically removed and if it ruptures before that, I’ll die. It gets a little bigger everyday, but I can’t afford the copays, so guess I’ll die?
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APPENDICES
Appendix A. Slider Comprehension

[ ] = slider, | = tick marks

Slider example:
Choice 1 50%  Choice 2
[-----------------] [-----------------] [-----------------]

Percentage comprehension task:
Prior to beginning the study, you will be required to complete 3 slider/percentage training questions, followed by a 4-question percentage comprehension test. If you do not pass the percentage comprehension test, you will be excluded from the study and ineligible for compensation. Please pay careful attention to the following examples and questions. This section should take less than 3 minutes. If you exit out of this survey, you will not be able to reopen it.

In the following questions you will be asked a series of questions involving ratios and the corresponding percentages associated with them. You will be using a slider bar to identify your answer. Understanding percentages is key to this study, as most questions will be in this format. Every answer will require to move or click the slider, even if it is already at the value you wish to choose. Below are some examples of how choosing between two options work in the context of this survey.

Here are some examples of making choices using the slider bar:

Choosing A 100% of the time, B 0% of the time
A 50% B
[-----------------] [-----------------]

Choosing A 75% of the time, B 25% of the time
A 50% B
[-----------------] [-----------------]

Choosing A 50% of the time, B 50% of the time
A 50% B
[-----------------] [-----------------]

Choosing A 25% of the time, B 75% of the time
A 50% B
[-----------------] [-----------------]

Choosing A 0% of the time, B 100% of the time
A 50% B
[-----------------] [-----------------] [-----------------]

You will now be tested on the above. Understanding the slider is necessary to continue onto the study. If you do not get all the four following questions correct you will be considered ineligible and removed from the study. You will only have one chance to answer these correctly, so please
pay attention to the questions carefully. You will not get compensated if you are removed from the study in this way.

Please move the sliders to the correct values in the following example questions

If you 100% would choose A over B, move the slider to the correct spot

A 50%  B

[---------------------------][---------------------------]

(correct answer)

A 50%  B

[--------------------------]

|---------------------------|---------------------------|

If you 100% would choose B over A, move the slider to the correct spot

A 50%  B

[---------------------------][---------------------------]

(correct answer)

A 50%  B

[--------------------------]

|---------------------------|---------------------------|

If you would choose A 50% of the time and B 50% of the time, move the slider to the correct spot

A 50%  B

[---------------------------][---------------------------]

(correct answer)

A 50%  B

[--------------------------]

|---------------------------|---------------------------|

If you would choose A 25% of the time and B 75% of the time, move the slider to the correct spot

A 50%  B

[---------------------------][---------------------------]

(correct answer)

A 50%  B

[--------------------------]

|---------------------------|---------------------------|

If you would choose A 75% of the time and B 25% of the time, move the slider to the correct spot

A 50%  B

[---------------------------][---------------------------]

(correct answer)

A 50%  B

[--------------------------]

|---------------------------|---------------------------|
Appendix B. Screener Possibilities

If 100% on comprehension:
You have successfully completed the screener.
(Followed by either Health Break or Monetary Discounting Break)

If less than 100% on comprehension:
We are sorry, you did not complete the following task correctly. We would like to thank you for your time and interest in the study. You will now receive a code to be compensated for your time.
Appendix C. Preambles Prior to Monetary and Health Decision-Making

**Monetary Discounting Break**
The following questions will consist of hypothetical choices between two monetary values that will vary in their likelihood or delay to getting the money. Answer these questions to the best of your ability and as if the situation were real. Note that there is no wrong way to answer these questions. You also have more freedom with the sliders for your choices.

**Health Break**
The following questions will ask you to imagine having experienced a particular symptom at a certain severity for some period of time. Assume that these symptoms are NOT related to COVID-19. Answer the following questions as if the situation were real. Note that there is no wrong way to answer these questions.
Appendix D. Symptom Concerns

With regard to nausea, what is your overall concern about experiencing…
  Mild Nausea
  Slider from 0 – 6, 0 being not at all concerned, 6 being very concerned
  Moderate Nausea
  Slider from 0 – 6, 0 being not at all concerned, 6 being very concerned
  Severe Nausea
  Slider from 0 – 6, 0 being not at all concerned, 6 being very concerned

With regard to coughing, what is your overall concern about experiencing…
  Mild Coughing
  Slider from 0 – 6, 0 being not at all concerned, 6 being very concerned
  Moderate Coughing
  Slider from 0 – 6, 0 being not at all concerned, 6 being very concerned
  Severe Coughing
  Slider from 0 – 6, 0 being not at all concerned, 6 being very concerned

With regard to headaches, what is your overall concern about experiencing…
  Mild Headaches
  Slider from 0 – 6, 0 being not at all concerned, 6 being very concerned
  Moderate Headaches
  Slider from 0 – 6, 0 being not at all concerned, 6 being very concerned
  Severe Headaches
  Slider from 0 – 6, 0 being not at all concerned, 6 being very concerned
Appendix E. Demographic Questions

Demographics survey:
Age: _______
Occupation: _______
Gender Identity: _______
Ethnic Identity (select all that apply):
• Asian
• Black/African
• Caucasian
• Hispanic/Latin
• Native American
• Pacific Islander
• Specify: ______
• Prefer not to answer

Highest level of education:
• Some high school
• High school diploma or equivalent
• Some university
• Associate’s degree
• Bachelor’s degree
• Some graduate school
• Master’s degree
• Doctoral degree

Annual Income: _______
Do you have employment other than MTurk?
• If yes,
  o What is your other employment?
• If no,
  o Did you lose your job due to COVID-19?
How often do you floss?
• At least once a day
• At least once a week
• At least once a month
• At least one in six months
• At least once a year
• Less than once a year

Health Insurance Status:
• Insured
• Not insured (If Insured then ask coverage):
  • If Medicaid/medicare move on to next question

Percent covered by insurance: _______
Co-pay amount: _______
• Uninsured
  • If uninsured is yes,
    • Did you lose health insurance due to COVID-19 related reasons (e.g., job loss, budget cuts, inability to pay for health insurance
    • If yes is selected,
      • Please describe the reason you lost your health insurance due to COVID-19
• Family’s/spouse’s insurance
Appendix F. SF-12 Survey

SF-12 Health Survey:


1. In general, would you say your health is:
   a. Excellent
   b. Very good
   c. Good
   d. Fair
   e. Poor

2. The following items are about activities you might do during a typical day, does your health now limit you in these activities? If so, how much? (Options of “Yes, limited a lot”, “Yes, limited a little”, and “No, not limited at all”)
   a. Moderate activities, such as moving a table, pushing a vacuum cleaner, bowling, or playing golf
   b. Climbing several flights of stairs

3. During the past 4 weeks, have you had any of the following problems with your work or other regular daily activities as a result of your physical health? (yes/no)
   a. Accomplished less than you would like
   b. Were limited in the kind of work or other activities

4. During the past 4 weeks, have you had any of the following problems with your work or other regular daily activities as a result of any emotional problems (such as feeling depressed or anxious)? (yes/no)
   a. Accomplished less than you would like
   b. Didn’t do work or other activities as carefully as usual

5. During the past 4 weeks, how much did pain interfere with your normal work (including both work outside the home and housework)?
   a. Not at all
   b. A little bit
   c. Moderately
   d. Quite a bit
   e. Extremely

6. These questions are about how you feel and how things have ben with you during the past 4 weeks. For each question, please give the answer that comes closest to the way you have been feeling. How much time in the past 4 weeks (all the time, most of the time, a good bit of the time, some of the time, a little bit of the time, none of the time).
   a. Have you felt calm and peaceful?
   b. Did you have a lot of energy?
   c. Have you felt downhearted and blue?

7. During the past 4 weeks, how much of the time has your physical health or emotional problems interfered with your social activities (like visiting with friends, relatives, etc.)?
   a. All of the time
b. Most of the time
c. Some of the time
d. A little of the time
e. None of the time
Appendix G. Fagerström Test for Nicotine Dependence

Do you smoke cigarettes?
- If yes, continue to Fagerström Test for Nicotine Dependence, else skip


1. How soon after you wake up do you smoke your first cigarette?
   a. Within 5 minutes
   b. 6 – 30 minutes
   c. 31 – 60 minutes
   d. After 60 minutes

2. Do you find it difficult to refrain from smoking in places where it is forbidden?
   a. Yes/no

3. Which cigarette would you hate most to give up?
   a. The first one in the morning
   b. All others

4. How many cigarettes a day do you smoke?
   a. 10 or less
   b. 11-120
   c. 21-30
   d. 31 or more

5. Do you smoke more frequently during the first hours after waking than during the rest of the day?
   a. Yes/no

6. Do you smoke if you are so ill that you are in bed most of the day?
   a. Yes/no
Appendix H. Trust in Medical Profession


1. Sometimes doctors care more about what is convenient for them than about their patient’s medical needs. (scoring is inverted for this question)
   a. Strongly Disagree
   b. Disagree
   c. Neutral
   d. Agree
   e. Strongly Agree

2. Doctors are extremely thorough and helpful.
   a. Strongly Disagree
   b. Disagree
   c. Neutral
   d. Agree
   e. Strongly Agree

3. You completely trust doctor’s decisions about which medical treatments are best.
   a. Strongly Disagree
   b. Disagree
   c. Neutral
   d. Agree
   e. Strongly Agree

4. A doctor would never mislead you about anything.
   a. Strongly Disagree
   b. Disagree
   c. Neutral
   d. Agree
   e. Strongly Agree

5. All in all, you trust doctors completely.
   a. Strongly Disagree
   b. Disagree
   c. Neutral
   d. Agree
   e. Strongly Agree
Appendix I. General Medical Questions

a. Have you ever avoided going to a doctor for an illness due to cost? (Yes/no)
b. Have you ever delayed going to a doctor for an illness due to cost? (Yes/no)
c. If yes to any of the above questions: Please describe in more detail your experience of delaying/refusing/avoiding some medical procedure/visit due to cost. (Open-ended comment)

Do you have an underlying health condition? (E.g., immunocompromised, blood disorder, metabolic disorder, diabetes, obesity)
   a. Yes/no
   b. If yes, what is the underlying condition?

Do you have a family member underlying health condition? (E.g., immunocompromised, blood disorder, metabolic disorder, diabetes, obesity)
   c. Yes/no
   d. If yes, what is the underlying condition?

Do you have any close friends with underlying health condition? (E.g., immunocompromised, blood disorder, metabolic disorder, diabetes, obesity, asthma)
   e. Yes/no
   f. If yes, what is the underlying condition?

Please comment on your decision-making during the previous tasks.
   Open-ended question.
Appendix J. Example Questions

**Probability and Delay Values Used**
Monetary Delay Values: 1 day, 1 month, 6 months, 1 year, 2 years
Monetary Probability values: 99%, 80%, 50%, 20%, 1%
Monetary Magnitudes: $500/$1000, $5000/$10000
Health Delay Values: 6 hours, 1 day, 1 week, 1 month, 6 months
Symptoms: Headache, nausea, cough
Severities: Mild, moderate, severe.
Health Costs: $10, $100, $1000

**Example Monetary-Discounting Questions**

**Gain Frame, Delay and Probability, Small Magnitude.**
“What is the likelihood that you would select gaining $1,000 in 6 months over a gaining $500 immediately?”

<table>
<thead>
<tr>
<th>Gain $500 immediately</th>
<th>Gain 1,000$ in 6 months</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>

“What is the likelihood that you would select a 20% chance of gaining $1,000 over a 100% chance of gaining $500?”

<table>
<thead>
<tr>
<th>100% chance of gaining $500</th>
<th>20% chance of gaining 1,000$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Loss Frame, Delay and Probability, Small Magnitude.**
“What is the likelihood that you would select losing $10,000 in 6 months over a losing $5,000 immediately?”

<table>
<thead>
<tr>
<th>Lose $5,000 immediately</th>
<th>Lose $10,000 in 6 months</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>

“What is the likelihood that you would select a 20% chance of losing $10,000 over a 100% chance of gaining $5,000?”

<table>
<thead>
<tr>
<th>100% chance of losing $5,000</th>
<th>20% chance of losing $10,000</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Example Health-Discounting Questions**
“You have been experiencing mild headaches for the past week. How likely are you to contact or see a healthcare professional for your symptoms?”

<table>
<thead>
<tr>
<th>0% chance of contacting/seeing</th>
<th>Mild headaches</th>
<th>100% chance of contacting/seeing</th>
</tr>
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for 1 week
“You have been experiencing severe nausea for the past 6 hours. How likely are you to contact or see a healthcare professional for your symptoms?”

0% chance of contacting/seeing healthcare professional

100% chance of contacting/seeing healthcare professional

---

Example Health and Monetary Discounting Questions

“You have been experiencing mild headaches for the past week. It will cost you $100 to contact or see a healthcare professional. How likely are you to contact or see a healthcare professional for your symptoms?”

0% chance of contacting/seeing healthcare professional at $100

100% chance of contacting/seeing healthcare professional at $100

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“You have been experiencing severe nausea for the past 6 hours. It will cost you $1000 to contact or see a healthcare professional. How likely are you to contact or see a healthcare professional for your symptoms?”

0% chance of contacting/seeing healthcare professional at $1000

100% chance of contacting/seeing healthcare professional at $1000

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Appendix K. IRB Approval

Date: October 13, 2020

To: Anthony DeFulio, Principal Investigator
Mark Rzeszutek, Student Investigator for dissertation

From: Amy Naugle, Ph.D., Chair
Re: IRB Project Number 20-10-16

This letter will serve as confirmation that your research project titled “Modeling Common Health Decisions with Behavioral Economics” has been approved under the exempt category of review by the Western Michigan University Institutional Review Board (IRB). The conditions and duration of this approval are specified in the policies of Western Michigan University. You may now begin to implement the research as described in the application.

Please note: This research may only be conducted exactly in the form it was approved. You must seek specific board approval for any changes to this project (e.g., add an investigator, increase number of subjects beyond the number stated in your application, etc.). Failure to obtain approval for changes will result in a protocol deviation.

In addition, if there are any unanticipated adverse reactions or unanticipated events associated with the conduct of this research, you should immediately suspend the project and contact the Chair of the IRB for consultation.

The Board wishes you success in the pursuit of your research goals.

A status report is required on or prior to (no more than 30 days) October 12, 2020 and each year thereafter until closing of the study. The IRB will send a request.

When this study closes, submit the required Final Report found at https://wmich.edu/research/forms.

Note: All research data must be kept in a secure location on the WMU campus for at least three (3) years after the study closes.
Appendix L. IRB Approved Changes

Western Michigan University

Human Subjects Institutional Review Board

Date: December 8, 2020

To: Anthony DeFulio, Principal Investigator
   Mark Rzeszutek, Student Investigator for dissertation

From: Amy Nangle, Ph.D., Chair

Re: WMU IRB Project Number 20-10-16

This letter will serve as confirmation that the changes to your research project titled “Modeling Common Health Decisions with Behavioral Economics” requested in your memo received December 4, 2020 (to revise compensation structure to use flat $3.50 compensation for completed survey; decrease training section of the screener to 3 questions; revise consent document to reflect these changes) have been approved by the Human Subjects Institutional Review Board.

The conditions and the duration of this approval are specified in the Policies of Western Michigan University.

Please note that you may only conduct this research exactly in the form it was approved. You must seek specific board approval for any changes in this project. You must also seek reapproval if the project extends beyond the termination date noted below. In addition, if there are any unanticipated adverse reactions or unanticipated events associated with the conduct of this research, you should immediately suspend the project and contact the Chair of the HSIRB for consultation.

The Board wishes you success in the pursuit of your research goals.

Approval Termination: October 12, 2021

291 W. Western Hull, Kalamazoo, MI 49008-5104
www.wmich.edu/hsirb, tel (269) 387-4131, fax (269) 387-8274