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# Monetary cost for time spent in everyday physical activities

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ABSTRACT

We measured utility curves for the hypothetical monetary costs as a function of time engaged in three everyday physical activities: walking, standing, and sitting. We found that activities requiring more physical exertion resulted in steeper discount curves, i.e., perceived cost as a function of time. We also examined the effects of gain vs. loss framing (whether the activity brought additional rewards or prevented losses) as well as the effects of the individual factors of gender, income, and BMI. Steeper discount curves were associated with higher income (annual household ≥ median of $45,000) and gain framing (which indicates loss aversion). There were interactions between gender and frame, and also income and frame: Females and higher income participants showed loss aversion whereas males and lower income participants were not affected by framing. Males showed less discounting in gain frames relative to females, whereas females showed less discounting in loss frames relative to males. In gain frames, higher income participants discounted more but in loss frames there was no effect of income. We also found individual tendencies for discounting across activities: if an individual exhibited steeper discounting for one activity, they were also more likely to exhibit steeper discounting for the other activities. These results have implications for designers of interventions to encourage non-exercise physical activities, suggesting that loss-framed incentives are more effective for women and those with middle class (or greater) incomes. Furthermore loss framed incentives have more uniform impact across income brackets because people discount loss frames similarly regardless of income whereas those with middle-class incomes are not as motivated by gain frames. Our results also demonstrate a general method for examining the costs of effort associated with everyday activities.



We regularly make decisions about the amount of physical exertion we are willing to undergo in everyday life. Is it worth walking an extra 10 min to buy cheaper produce? Is it worth standing in line for 20 min to obtain a refund? The small decisions potentially add up to big health implications: lack of physical exertion in our everyday activities, also known as non-exercise activity thermogenesis (NEAT), has been implicated (along with increased caloric intake) as one of the main causes of recent increase in obesity in first world countries (Levine et al., 2006). Research shows that NEAT accounts for up to 2/3 of daily energy expenditure when compensating for increased caloric intake (Levine et al., 1999). It is estimated that lean individuals spend 2.5 h per day more standing and walking than obese individuals, which is an additional expenditure of approximately 350 additional calories a day (Levine et al., 2006). Thus, NEAT offers a promising avenue for weight management. However, it remains unknown the extent to which NEAT offers an 'easy' weight management solution. While NEAT activities may appear to require less concerted effort and thus appear more achievable than scheduling dedicated exercise sessions, non-exercise activities still involve potential 'costs', such as physical or mental effort, unpleasant experiences (e.g., boredom, discomfort), and time.

The costs associated with activities can be evaluated using recent frameworks in behavior science, where a wide body of research has made it increasingly clear that most of behavior can be explained as a series of decisions that are underpinned by a valuation of choice options. One method of assessing value is to measure expected value (perceived utility) curves. Here, a binary choice task is used to determine subjective indifference points. These results can be plotted as curves on a graph showing different reward scenarios that perceived to be of equal preference. Typically these curves show how the perceived utility of a given amount of reward

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is decreases as a function of different amounts of some trade-off, or 'cost', which diminishes perceived reward value.

A large body of highly profiled research has used such perceived utility curves to examine how factors of delay and uncertainty associated with a reward decrease the reward's perceived value, known as delayed and probabilistic discounting. Many studies have examined factors of delay and probability together (Du et al., 2002; Estle et al., 2007; Green and Myerson, 2004; Killeen, 2009; Rachlin et al., 1991; Radu et al., 2011; Weller et al., 2008a; Yi et al., 2006; Heyman and Gibb, 2006; Petry, 2012; Reynolds, 2006). Another relatively less used approach is to measure utility curves to examine the perceived costs of behaviors and activities. Here the utility curves represent how much less reward a person is willing to take if they could avoid the behavior, thus providing a measure of the cost of that behavior. For example, if a person has equal preference for a \$90 reward and a \$100 reward that also requires them to stand in line for half an hour, assuming both rewards are eventually received at the same time (no difference in delay of receipt), one can estimate that the cost of standing in line for half an hour costs is about \$10 in the context of the \$100 reward. By measuring the indifference points for varying amounts of behavior, one can measure the perceived cost associated with different amounts of behavior. Examples of behavioral costs include physical and/or mental discomfort associated with the effort required, as well as the opportunity costs of time spent on the behavior.

In contrast to the extensive research on the costs of delayed and probabilistic rewards, there have been only a few studies examining the costs of engaging in uncomfortable behaviors and effortful activities. Here, in analogy to the terms probabilistic and delayed discounting, researchers have used the phrase 'effort discounting' (Hartmann et al., 2013; Mitchell, 2004; Reed et al., 2011). One such study examined the cost of decision making (Reed et al., 2011), where discounting (i.e., perceived cost) was observed as the number of options increased. Other studies have examined discounting in response to intensity of physical effort (e.g., squeezing of hand dynamometer) (Hartmann et al., 2013), and have found this differed for smokers and non-smokers (Mitchell, 1999) and cigarette deprived smokers (Mitchell, 2004). Another type of discounting, which also relates to the cost of effort, is activity discounting, where costs are evaluated for the perceived effort for engaging in an activity over time. The measurement of the cost of effort over time differs from the cost of 'effort intensity': the latter evaluates the costs of effort over a fixed time as the intensity of the behavior varies, whereas the former evaluates the costs of participation in a behavior over varying time while the intensity of the behavior is fixed. Discounting in response to activity effort has been examined for the hypothetical task of cleaning Japanese bathtubs (Sugiwaka and Okouchi, 2004), and found that discounting in relation to numbers of tubs cleaned was not related to delay discounting, nor measures of reformative self control.

Typically, previous studies in probabilistic and delayed discounting (Du et al., 2002; Estle et al., 2007; Green and Myerson, 2004; Killeen, 2009; Rachlin et al., 1991; Radu et al., 2011; Weller et al., 2008a; Yi et al., 2006; Heyman and Gibb, 2006; Petry, 2012; Reynolds, 2006), as well as effort discounting (Sugiwaka and Okouchi, 2004; Reed et al., 2011; Mitchell, 2004) (with the exception of (Hartmann et al., 2013)), have found discount curves to follow a characteristically hyperbolic function:

$$Y = A/(1+bX)^S \tag{1}$$

where $Y$ represents the subjective value of the reward of amount $A$, $b$ is the parameter that governs the rate of discounting, $X$ is some increasing currency of cost, and $S$ is the scaling of the curve. One benefit of fitting curves to this function is that the parameters allows researchers to quantify severity of discounting, which is how rapidly reward values decline as a function of increasing cost $X$. Another method for quantifying the amount of discounting is to calculate the area under the experimentally measured discounting curve (Myerson et al., 2001; Estle et al., 2007). Here, the area under two consecutive subjective value points is computed according to the trapezoid rule as follows:

$$(b-a)(f(a)+f(b))/2 \tag{2}$$

where $a$ and $b$ are subjective values at consecutive points. The area under the curve is then obtained by adding together the area under all consecutive subjective value points. This area can also be used to capture how steeply the reward was discounted, with smaller areas indicating greater discounting.

In our current work, motivated by the ubiquity of non-exercise activity and its relevance to weight, we use the method of measuring perceived utility curves to examine the following question: How costly do people perceive everyday non-exercise physical activities to be? In particular we measured discounting as a function of time engaged in three primary everyday physical activities that vary in terms of physical exertion required: walking, standing in line, and waiting while sitting. Here, each individual discount curve will reflect the cost of engagement as a function of time spent in the activity, with the intensity of the behavior assumed to be constant. Thus, each of our resultant discount curves will reflect perceived costs over time spent engaged in an activity with fixed intensity, but we measure these curves for three activities of varying intensity. We also examined the effects of framing because research has shown that people react differently to choice scenarios involving losses vs. gains, such as the phenomenon of loss aversion, where losses have been found in some circumstances to be more psychologically powerful than gains of equal magnitude (Banks et al., 1995; McCormick and McElroy, 2009; O'Keefe and Jensen, 2008; O'Keefe and Jensen, 2009; Volpp et al., 2008). Finally, we also examined discounting is influenced by the individual variables of income, gender, and whether one is overweight. To address these questions we measured discount curves for time spent in various activities, as has been done in previous work mentioned above (Sugiwaka and Okouchi, 2004; Reed et al., 2011; Field et al., 2006; Mitchell, 2004).

## 1. Method

### 1.1. Participants

Online participants ($n = 166$) recruited from Amazon Mechanical Turk were paid \$.50 to complete the experiment in 2012. The location of participants was restricted to the US because we wanted to reduce confounds due to English comprehension and culture and US was the largest user base on Amazon Turk. Six participants did not pass our criteria of paying adequate attention established by our catch trials (see below), leaving us with 160 participants total, 78 of which were male. Random assignments into loss vs. gain framing conditions (see below) resulted in 39 males in each of the two conditions. The age of participants ranged from 18 to 70 years and the median age was 31. Participants' mean BMI = 26.6 with SD = 6.6. Total number of overweight participants (BMI > 25) was 84. Overweight was determined by the cut-off BMI stipulated on sites from major health organizations such as National Health Services (2013) and the Center for Disease Control and Prevention (2013). Previous work has found that self-report of BMI has been found to be valid for epidemiological studies but needs more careful adjustments when trying for precise measures of obesity prevalence (Gorber et al., 2007; McAdams et al., 2007). As our study only aims to compare differences in activity costs between