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Comparison of delay discounting of different outcomes in cigarette smokers, smokeless tobacco users, e-cigarette users, and non-tobacco users

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Abstract

Delay discounting is the process by which a commodity loses value as the delay to its receipt increases. Rapid discounting predicts various maladaptive behaviors including tobacco use. Typically, delay discounting of different outcomes has been compared between cigarette smokers and nonsmokers. To better understand the relationship of delay discounting to different modes of tobacco use, we examined the differences in delay discounting of different outcomes between cigarette smokers, smokeless tobacco users, e-cigarette users, and non-tobacco users. In the present study, all participants completed 8 titrating delay-discounting tasks: \$100 gain, \$500 gain, \$500 loss, alcohol, entertainment, food, a temporary health gain, and a temporary cure from a disease. Non-tobacco users discounted most outcomes less than tobacco users overall; however, there were no differences in discounting among the different types of tobacco users. These results suggest that nicotine consumption of any kind is associated with a higher degree of impulsivity compared to non-tobacco users. Adoption of tobacco products that have been perceived as less harmful (e.g., e-cigarettes) is not associated with a baseline difference or decrease in delay discounting if adopted after a history of cigarette use.

Keywords

delay discounting; impulsivity; electronic cigarettes; decision-making; nicotine; cigarettes

The personal and societal consequences of cigarette smoking are staggering. Despite historic decreases, cigarette smoking is the leading cause of preventable mortality, causing more than 480,000 deaths each year in the U.S. (CDC, 2017; Mokdad et al., 2005). Evidence suggests that acquisition and maintenance of cigarette smoking is not from lack of knowledge regarding the probable health consequences (Oncken et al., 2005). Instead, a behavioral

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Supporting Information

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process, delay discounting, has frequently been associated with cigarette smoking and may play an etiological role (Audrain-McGovern et al., 2009).

Delay discounting is the process by which an outcome loses value as the delay to its receipt increases, and encompasses choice between immediate and delayed outcomes (Odum, 2011a). Delay discounting has been referred to as a transdiagnostic process (Bickel et al., 2019), because it underlies multiple maladaptive behaviors (Amlung et al., 2017; MacKillop et al., 2011; Snider et al., 2019) including cigarette smoking (Bickel et al., 1999), alcohol abuse (Strickland et al., 2019), and opioid abuse (Karakula et al., 2016; Madden et al., 1997). Delay discounting also predicts engagement in a range of other health behaviors including tanning (Sheffer et al., 2018), seatbelt use (Daugherty & Brase, 2010), texting while driving, and financial decision-making (Snider et al., 2019).

Cigarette smoking can be conceptualized, in part, as choosing between the immediate psychophysical effects of nicotine and the delayed consequences of consuming combustible tobacco. A large body of research has demonstrated that cigarette smokers discount delayed outcomes more than nonsmokers do (e.g., Bickel et al., 1999; Mitchell, 2004). Delay discounting can also differentiate the severity of nicotine dependence (Sweitzer et al., 2008) and predict relapse (González-Roz et al., 2019). This relative insensitivity to delayed consequences in cigarette smokers has also been observed for a variety of outcomes including money, food (Friedel et al., 2014), and non-consumable outcomes such as health (Friedel et al., 2016).

Over the past decade, the tobacco product marketplace has become increasingly complex as the popularity of electronic cigarettes has grown (McMillen et al., 2014). Białaszek et al. (2017) compared monetary delay discounting between cigarette smokers, e-cigarette users, and non-tobacco users. Cigarette smokers and e-cigarette users discounted similarly, and both groups showed steeper discounting than non-tobacco users. Weidberg, Gonzalez-Roz, Martinez-Loredo et al. (2017) found the same ordinal relationship between discounting of money in cigarette smokers, e-cigarette users, and nonsmokers, though the differences were not statistically significant (possibly due to a low sample size).

What is particularly unclear is if the observed differences between e-cigarette users and non-tobacco users generalize to other outcomes, such as food or health outcomes, in a similar way as the observed differences between cigarette smokers and non-tobacco users (Friedel et al. 2014; Friedel et al. 2016). That is, do e-cigarette users discount a variety of outcomes more steeply than do nonsmokers? Such a finding would suggest that nicotine consumption, and not necessarily the associated risk of cigarette consumption, is associated with elevated delay discounting. Moreover, no research has examined other methods of nicotine consumption such as smokeless tobacco use.

The purpose of this study was to expand our understanding of the role of nicotine consumption in delay discounting by comparing delay discounting between four groups: cigarette smokers, e-cigarette users, smokeless tobacco users, and non-tobacco users. We hypothesized that tobacco consumption, regardless of vehicle, would be associated with higher delay discounting rates across most outcomes tested. An additional goal was to

replicate and extend previous findings that smokers discount monetary and nonmonetary outcomes more steeply than non-nicotine users, given the importance of replication in the behavioral sciences (e.g., Open Science Collaboration, 2015; Wingen et al., 2020).

Method

Participants

The Utah State University Institutional Review Board approved all procedures and written informed consent was obtained for all participants. Participants were recruited through a combination of newspaper and radio advertisements, flyers, and word of mouth referrals. Potential participants first completed a telephone screen to determine initial eligibility. Participants younger than 21 years old or that reported no alcohol use were disqualified. Participants were asked whether they smoked cigarettes (and if so, how many per day), whether they used smokeless tobacco, and whether they used e-cigarettes. Participants were classified as “nonusers” if they did not use smokeless tobacco or e-cigarettes and had smoked less than 100 cigarettes in their lifetime. Participants were classified as “smokeless tobacco users” if they reported daily use of smokeless tobacco, no use of cigarettes within the previous year, and no past cigarette use exceeding two tobacco cigarettes a day. These criteria were chosen because exclusive smokeless tobacco use is uncommon (Sung et al., 2016; Cheng et al., 2017). Participants were classified as “smokers” if they reported smoking 10 or more cigarettes per day. Participants were classified as “e-cigarette users” if they reported daily use of e-cigarettes but no use of cigarettes or smokeless tobacco. E-cigarette users were included if they were ex-smokers (i.e., had quit smoking cigarettes at least 1 year ago). All of the included e-cigarette users were ex-smokers. Qualifying participants were invited to the laboratory for additional screening and testing. A total of 30 nonusers, 37 smokers, 20 smokeless tobacco users, and 15 e-cigarette users completed the study, making the total sample size 102. A power analysis ($\alpha = .05$, power = .8, $f = 0.15$) indicated that a total sample size of 64 participants would be needed to detect a small-medium effect. In order to detect a large effect ($f = 0.40$), a total sample size of 12 participants would be needed.

Procedure

Data collection occurred in a quiet, private office with no windows. Participants completed all tasks within a single session while seated at a desk with a computer. Participants were compensated \$30 for completing the approximately 1-hr session. After the informed consent was signed, two biological samples were collected. The first sample, administered through the FC 10 Breathalyzer (Lifeloc), measured recent alcohol consumption. Any participant with a blood-alcohol level above 0.000 was not included in the study (one participant was excluded). The second sample, administered with a Micro+ Smokerlyzer (Bedfont Scientific LTD.), measured carbon monoxide (CO) as an indication of recent cigarette use. Reported smokers had to measure a CO level of 6 ppm or higher (Bedfont Scientific n.d.) to qualify. All smokers met this criterion. Additionally, e-cigarette users were asked to show their e-cigarette and the e-cigarette’s model and voltage were recorded.

Delay Discounting Tasks—Participants then read instructions on the computer similar to those described in Odum et al. (2006) prior to completing eight different delay discounting tasks. The delay discounting tasks were separated into two blocks of four tasks. In each block, participants first completed a 10-question practice block with money. Block 1 contained monetary gain (\$100), food, entertainment, and alcohol delay discounting tasks, and Block 2 contained monetary gain (\$500), monetary loss (\$500), temporary health boost, and temporary health cure delay discounting tasks. The presentation of each Block was randomized with a 5-min break in between. The order of presentation of each delay discounting task within each block was also randomized for each individual. For each delay-discounting task, six indifference points (the point at which a quantity of the immediate outcome was subjectively equivalent to the larger–delayed outcome) were obtained for each individual.

These amounts and outcomes were chosen for two reasons. First, we sought to extend and replicate previous research by Friedel et al. (2014) and Friedel et al. (2016) in which \$100 of consumable outcomes and \$500 of health outcomes were used, respectively. Second, we wanted to ensure that each outcome amount was presented in meaningful amounts. For example, \$100 of healthcare may not be a particularly large amount relative to typical healthcare costs in the U.S.A. For that reason, we choose the larger but still modest amount of \$500. Likewise, for food and alcohol, we chose the smaller amount of \$100 to present more feasible servings of those outcomes.

Monetary Gain (\$100). In the monetary gain (\$100) task, indifference points were obtained at six different delays to the larger–later reward, presented in the following order: 1 week, 2 weeks, 1 month, 6 months, 5 years, and 25 years. For this task, the first question was, “Would you prefer \$50 now or \$100 in (delay)?” The positioning of the immediate and delayed options alternated randomly across the right and left positions of the computer screen. Participants used the mouse to choose one of the two options. After each question, the amount of the immediate reward was adjusted according to the titration procedure outlined by Du et al. (2002) and Frye et al. (2015). If the smaller–sooner reward was selected (or forgone), the amount of that reward was decreased (or increased) by \$25 in the next choice trial. Subsequent adjustments to the immediate reward were 50% of the preceding adjustment. The amount of the immediate reward following the 10th choice trial was used as the indifference point for that delay. At each subsequent delay, this process was repeated. All values displayed to participants were rounded to the nearest penny (\$0.01).

Food. As with money, the indifference point in the delay discounting tasks for food was determined by a 10-trial titration procedure and all values were rounded to the nearest 100th. For these tasks, the participant was asked to name their favorite food and how much it cost. The reported cost was then divided into \$100, and the quotient served as the larger–later reward amount throughout that discounting task, similar to the procedure first used by Odum and Rainaud (2003). The initial amount of the smaller–sooner reward was half the amount of the larger–later. For example, if a participant indicated that their favorite food was a hamburger and that it cost \$5, their first question would read “Would you prefer 10 hamburgers now or 20 hamburgers in 1 week?” From there, the titration procedure outlined

above was used to obtain indifference points for that commodity at each delay. Across outcomes, all indifference points were scaled by the amount of the larger, later outcome so that all indifference points reported are standardized between 0 and 1.

Entertainment.: The procedure for the entertainment task was identical to the food task, except that participants were asked to report their favorite form of entertainment (e.g., MP3s) and the cost, and subsequent questions were based on those responses.

Alcohol.: The procedure for the alcohol task was identical to the food and entertainment tasks, except that participants were asked to report their favorite alcoholic beverage (e.g., beer) and the cost, and subsequent questions were based on those responses.

Monetary Gain (\$500).: All procedural details for the monetary gain (\$500) task were the same as the monetary gain (\$100) task, except that the larger–later reward was always \$500 instead of \$100, and the starting amount for the smaller–sooner reward was \$250.

Monetary Loss (\$500).: The discounting task for a monetary loss was identical to the monetary gain tasks, but the phrase “to lose” was inserted before each option (e.g., “Would you prefer to lose \$250 now or to lose \$500 in 1 year?”). The amount of the immediate loss was then adjusted similarly to monetary gain tasks.

Health Boost.: For the health boost delay discounting task, participants read the following vignette (Friedel et al., 2014; Odum et al., 2002):

I want you to think about your health over the past month. Now I want you to imagine that you have a choice between receiving some amount of money and temporarily feeling 10% better. That means you would feel more alert, have more energy, be physically stronger, have less body fat, and be less likely to become sick. However, this 10% increase in your health would only be temporary and then you would return to your current state of health. Receiving \$500 right now would be just as attractive as experiencing how much time of 10% better health?

In other words, participants were asked to report how much of a temporary health boost would be equal to \$500. Participants then typed a number and a unit of time (e.g., days, weeks, months, years). After the selection was confirmed, the procedure was identical to the previous tasks. For example, if the participant reported that a 6-month health boost would be equivalent to \$500, the first question presented would be, “Would you prefer a 3-month health boost now or a 6-month health boost in one week?” The delay progression and titration procedures were the same as in previous tasks.

Health Cure.: For the health cure delay discounting task, participants read the following vignette (Friedel et al., 2014; Odum et al., 2002):

For the last 2 years, you have been ill because at some time in the past you had unprotected sex with someone you found very attractive, but whom you did not know. Thus, for the past 2 years, you have come down with a lot of colds and other ailments, some of which have required hospitalization. You have lost a lot of weight

and are getting increasingly thin. Some friends do not come to see you anymore because of your disorder and those that do feel uncomfortable being with you. Imagine that without treatment you will feel this way for the rest of your life and that you will not die during any of the time periods described here. Receiving \$500 right now would be just as attractive as experiencing how much time of a cure?

As in the health boost task, participants reported the duration of a cure that would be equal to \$500. Other details were as in the health boost task.

Questionnaires—At the end of the session, participants completed a series of questionnaires and tasks on the computer. Questionnaires and tasks were programmed using E-Prime 2.0® computing software. Participants completed the South Oaks Gambling Screen (SOGS; Lesieur and Blume 1987), which is a 36-item questionnaire that measures gambling behavior (scores range from 0–20). The Alcohol Use Disorders Identification Test (AUDIT; Saunders et al., 1993) was also completed, and is a 25-item questionnaire that identifies alcohol abuse in respondents using “yes” or “no” questions (scores range from 0–53). The Information Inventory (II; Moon and Gorsuch, 1988) was also administered and is a 13-item IQ questionnaire that asks a variety of questions ranging from events in history to vocabulary (scores can range from 0 to 30). Participants also provided demographic information including age, ethnicity, gender, marital status, income, and education.

Analysis

Demographic variables were compared across groups with Chi-Square or one-way ANOVAs, depending on the nature of the data. If there were significant differences across the groups in demographic variables (i.e., a main effect of group membership), we conducted post hoc comparisons using Tukey’s method. Any statistically significant differences in the demographic variables were included as covariates in the model to compare the degree of discounting (described below).

To compare the degree of discounting across both group and outcome type we used a Generalized Estimating Equation (GEE; Friedel et al., 2019; Hanley et al., 2003). A GEE is a statistical model designed to account for potentially autocorrelated data that exist in clusters. A GEE is similar to a mixed-effects model, but the focus of a GEE is on different population-level effects whereas the focus of a mixed-effects model is explaining how each cluster is different. For this reason, the results of our GEE model can be treated as similar to a mixed-effects ANOVA. A GEE was also selected because it is more robust for data with unbalanced group sizes. To summarize the effects of the categorical differences (i.e., group membership, outcome type) we calculated Wald statistics which are similar to the main effects and interaction effects of an ANOVA. We separately conducted post hoc comparisons on mean indifference points (adjusted for the covariates) across group and across outcome type. Importantly, preliminary analysis did not identify any differences in discounting between the different tobacco-use groups. Therefore, to increase the power of our statistical analyses, these groups were combined into one tobacco-users group that was then compared to non-tobacco users.

We also calculated correlation coefficients using the mean indifference point for each participant and outcome type (i.e., eight mean indifference points per participant). The distribution of mean indifference points appeared normal based on skew, kurtosis, and visual inspection of Q-Q plots. Therefore, we report Pearson's r .

Finally, we applied an algorithm for identifying nonsystematic delay-discounting data (Johnson & Bickel, 2008). The first criterion identifies data sets in which there is at least one indifference point that is larger than the previous indifference point by 20% of the larger, later amount. The second criterion identifies data sets in which the final indifference point is not 10% of the larger, later amount lower than the first indifference point. The average percentage of task results failing either criterion was 22%. For the monetary outcomes, 19% of the \$500 loss task results failed the second criterion (the highest percentage for all monetary tasks for both criteria). For the nonmonetary outcomes, 37% of the food task results failed the second criterion (the highest percentage for all nonmonetary tasks for both criteria). We elected not to remove participant data from the final analyses, however, as in Friedel et al. (2014), due to the within-subjects nature of the experimental design. Otherwise, if a participant met exclusion criteria for one outcome, all of their data would need to be excluded, which would result in substantial loss of systematic data. The pattern of results was the same regardless of whether data from participants with unsystematic data were included or excluded.

Results

Demographic characteristics and questionnaire scores for nonusers, smokers, smokeless tobacco users, and e-cigarette users are reported in Table 1. A Chi-square test did not reveal differences in the distribution of sex or race across the groups. Separate one-way ANOVAs did reveal differences in age ($F_{(3,98)} = 5.47, p = .002$), AUDIT scores ($F_{(3,98)} = 3.61, p = .016$), and carbon monoxide readings ($F_{(3,97)} = 45.99, p < .001$). For age, Tukey's test indicated e-cigarette users were significantly younger than cigarette smokers ($MD = -14.27, p = .001$), smokeless tobacco users ($MD = -13.32, p = .008$), and nonusers ($MD = -11.97, p = .011$). The post-hoc analysis indicated there were no differences in age across cigarette smokers, smokeless tobacco users, and nonusers. For AUDIT scores, Tukey's test revealed that AUDIT scores were only different between cigarette smokers and nonusers ($MD = 4.15, p = .318$). For CO readings, Tukey's test revealed that cigarette smokers had significantly higher CO readings than nonusers ($MD = 9.42, p < .001$), smokeless tobacco users ($MD = 6.19, p < .001$), and e-cigarette users ($MD = 7.12, p < .001$). There were no significant differences in CO readings between nonusers, smokeless tobacco users, and e-cigarette users. For our statistical analyses, age and AUDIT scores were included in the models as covariates.

We identified differences in indifference points across groups and outcomes using a GEE analysis. We used an autoregressive correlation matrix for the GEE because of an observed trend of decreased correlation in indifference points as time between indifference points increased. An exploratory model included age and AUDIT scores as main effects, but these variables did not significantly affect indifference points. To report the most parsimonious

model, we removed age and AUDIT scores from the GEE analysis but we retained them as covariates for pairwise comparisons.

Both type of nicotine use (non-, smoking, e-cigarette, and smokeless) and the delayed outcome affected indifference points (Fig. 1; see online Supplemental Table for means, SDs, and SEMs of all indifference points for each task and group). As both nicotine use and delayed outcome type were nominal variables, direct interpretation of the β coefficients from the GEE is complicated because all of the coefficients describe differences between the factor of interest and an arbitrarily designated reference group. For a summary of the whole GEE model, we calculated Wald statistics for the GEE model (R ANOVA function). The Wald statistics can be considered to determine if a main effect is present for the coefficients associated with a nominal variable (i.e., nicotine use, outcome type). In other words, the Wald statistics were used to determine if type of nicotine use as a whole and delayed outcome type as a whole affected indifference points (e.g., a main effect of nicotine on indifference points). We found that nicotine use affected indifference points ($\chi^2(3) = 15.87$, $p = .001$) and that the delayed outcome affected indifference points ($\chi^2(7) = 191.64$, $p < .001$). This analysis also revealed that delay significantly affected indifference points ($\chi^2(1) = 446.75$, $p < .001$). The analysis did not detect a significant omnibus interaction between type of nicotine use and delayed outcome type on indifference points. However, the χ^2 values should be interpreted with caution, as they only indicate that type of nicotine use, delayed outcome type, and delay significantly affected indifference points. To determine the degree and sign of the differences across these factors we used pairwise comparisons.

Table 2 contains the differences in the mean adjusted-indifference points for each pairwise group. The mean adjusted-indifference points were aggregated across all eight of the different delayed outcomes. Therefore, the values in Table 2 represent the pairwise differences in the mean (adjusted) indifference point averaged across all of the outcomes. For example, the upper-left cell contains the mean adjusted-indifference points for nonusers minus the mean adjusted-indifference points for cigarette smokers. Across all eight outcomes, nonusers had indifference points that were, on average, 0.15 higher than cigarette smokers. Mean adjusted-indifference points for nonusers were significantly higher than mean adjusted-indifference points for cigarette smokers ($MD = 0.14$, $p = .020$), smokeless tobacco users ($MD = 0.15$, $p = .019$), and e-cigarette users ($MD = 0.15$, $p = .025$). For the pairwise comparisons between the different groups of nicotine users, there were no significant differences in mean adjusted-indifference points. Therefore, the significant Wald statistic for nicotine use was caused by the nonusers having mean adjusted indifference points that were significantly higher than the nicotine users. Because we did not find a difference in discounting between the three nicotine groups, subsequent analyses report the comparisons between nonusers and the collapsed nicotine users group.

Table 3 contains the differences in the mean adjusted-indifference points for each relevant pairwise delayed outcome. The relevant comparisons were 1) pairwise comparisons between \$100, alcohol, entertainment, and food; 2) pairwise comparisons between \$500, \$500 loss, temporary health boosts, and temporary cures, and finally 3) a comparison of mean adjusted-indifference points between \$100 and \$500. Across the groups, mean adjusted-indifference points for \$100 were higher than mean adjusted-indifference points for alcohol ($MD = 0.18$,

$p < .001$), entertainment ($MD = 0.16, p = .002$), and food ($MD = 0.19, p < .001$). Across each pairwise combinations of alcohol, entertainment, and food, there were no significant differences in mean adjusted-indifference points. For the second set of relevant comparisons, adjusted-indifference points were lower for temporary cures than for a \$500 loss ($MD = -0.09, p = .041$). Across the other relevant pairwise comparisons, there were no significant differences in adjusted-indifference points. Finally, indifference points for \$100 were significantly lower than indifference points for \$500 ($MD = -0.17, p < .001$).

We also conducted a second GEE with the cigarette smokers, smokeless tobacco users, and e-cigarette users collapsed into a single “nicotine user” group, because there were no significant differences in the mean indifference points for each nicotine using group, and there were significant differences in the mean indifference points between each respective group and the nonuser group (Table 2). Across outcome types, indifference points for nonusers were significantly higher than indifference points for nicotine users ($MD = 0.147, p = .002$). Table 4 displays the mean differences between nicotine users and nonusers for each outcome type and Figure 1 displays the median indifference points. Nonusers had significantly higher indifference points for \$100 (Panel a), entertainment (Panel c), and food (Panel d). There were no significant differences between the groups for alcohol (Panel b). Nonusers had significantly higher indifference points for \$500 (Panel e), the temporary boost in health (Panel h), and the temporary relief from a debilitating disease (Panel g). There were no significant differences between the groups for the \$500 loss (Panel f).

Table 5 displays the Pearson’s correlation coefficients between the mean indifference points for each outcome type. In general, there were strong positive correlations in the degree of discounting across outcome types. These correlations indicate that a person who more steeply discounts one outcome type is likely to more steeply discount other outcome types. The opposite is also true: a person who more shallowly discounts one outcome type is more likely to more shallowly discount other outcome types. Out of the 28 pairwise combinations of correlations, the only correlations in mean indifference point that were not statistically significant were 1) alcohol and entertainment, 2) a loss of \$500 and entertainment, and 3) a loss of \$500 and a temporary boost in health. The correlations that were not statistically significant were all small, positive (in the same direction as the statistically significant ones), and likely capture relatively smaller effects (see Cohen, 1992).

Discussion

We assessed delay discounting across various outcomes for nicotine users and nonusers. For money, food, entertainment, and health, delay-discounting rates were greater for nicotine users than nonusers. In other words, nicotine users were more likely to choose the smaller-sooner outcome over the larger-later outcome across each of these outcomes. This effect was apparent across participants who smoked cigarettes, used e-cigarettes, and used smokeless tobacco. The initial purpose of this study was to investigate differences in delay discounting among different tobacco product users. However, the similarities in discounting across groups of participants who used tobacco indicate that the mode of nicotine delivery may not be strongly related to the degree of delay discounting. Instead, the relevant factor seems to be tobacco use in any form; those who use tobacco tend to discount various

delayed outcomes more steeply than nonusers. These data do not speak to whether this relation is causal. Delay discounting may play an etiological role in smoking acquisition (e.g., Audrain-McGovern et al., 2009). It is also possible that nicotine use itself contributes to steeper delay discounting, such that any nicotine use elevates discounting.

The finding that participants who use nicotine discount delayed outcomes more steeply than participants who do not replicates and extends previous research, which is important in itself given concerns regarding replicability in behavioral science (Open Science Collaboration, 2015; Shrout & Rodgers, 2018). Several studies have shown that cigarette smokers discount delayed outcomes more steeply than nonsmokers for money (e.g., Bickel et al., 1999; Mitchell, 2004), food and entertainment (Friedel et al., 2014), and health (Friedel et al., 2016). Our data are consistent with these prior studies including previous work demonstrating that e-cigarette users discount money more than nonnicotine users (Białaszek et al., 2017). Importantly, we extended these differences between e-cigarette users and non-nicotine users to different nonmonetary outcomes. We also expanded the scope of the relation between nicotine consumption to delay discounting to include smokeless tobacco users. We found no differences in discounting across groups for alcohol or monetary loss, which replicates previous research (Friedel et al., 2014; 2016). E-cigarette users and smokeless tobacco users resemble cigarette smokers in terms of relatively steep delay discounting of a variety of outcomes compared to nonusers. Importantly, despite the limited sample size of those three groups, our results justify their collapse into a single “nicotine” group. Given the obtained effect size of the interaction of nicotine product type (e.g., smoker vs. e-cigarette vs. smokeless) and delay discounting outcome ($\eta^2 = 0.011$), a sample size of over 9,000 participants would be needed to detect a statistically significant interaction and show that the nicotine groups differ. The lack of difference in delay discounting among different tobacco product users may reflect a general tendency to engage in risky behaviors (e.g., nicotine consumption of any form). Further research is needed to better understand the homogeneity of discounting among tobacco users reported here.

Indirectly, these results speak to the value of null findings to inform our understanding of basic behavioral processes (Ferguson & Heene, 2012). Psychology and science as a whole have primarily focused on the publishing of “positive” results. Our “null” results of the same degree of delay discounting among different types of tobacco users contribute to our understanding of the role of delay discounting in tobacco consumption and maladaptive decision making in general.

One limitation of this study is that it is possible that the sample is not representative. This sample of participants were all residents in Utah, which has the lowest rate of cigarette use in the US (CDC, 2018). Additionally, all electronic cigarette users in the current study reported a tobacco smoking history. This may be a limitation of our study because the features of the groups may have some overlap. Previous research has demonstrated a difference in discounting between ex-smokers and current smokers, but no difference between ex-smokers and never smokers (e.g., Bickel et al., 1999). In the current study, however, ex-smokers who currently use electronic cigarettes discounted to a greater degree than nonusers and did not discount differently from individuals who use other types of nicotine delivery systems. This finding suggests that ex-smokers who no longer use nicotine

may differ from ex-smokers using electronic cigarettes or other nicotine delivery systems, confirming previous findings (Weidberg, Gonzalez-Roz, & Secades-Villa, 2017). It could be that complete cessation of nicotine use is associated with a decrease in delay discounting, or it could be that only people with a low degree of discounting are able to completely cease using nicotine. To help clarify this issue, a future study that recruits a more nationally representative sample would be illuminating. Furthermore, a study that compares discounting across different commodities in never-users, ex-users/nonusers, current cigarette smokers who have not used electronic cigarettes, and current electronic cigarette users who have never smoked cigarettes would be beneficial.

A second limitation is the need to better differentiate between different types of nicotine users. In the present study, we used breath CO and required e-cigarette users to show their e-cigarette device. In addition, the screening survey did not present “right” or “wrong” answers, so we feel confident that our groups were accurately divided. However, additional measures such as salivary cotinine (a metabolite of nicotine) would increase the confidence in the accuracy of group membership.

A final limitation is the selection of \$500 as the outcome for the monetary loss condition even though the nonmonetary outcomes were derived from \$100. There were several factors that affected our decision. First, we were most interested in comparing monetary losses to monetary gains, and not necessarily in comparing monetary losses to nonmonetary outcome gains. Second, we also wanted to increase the variety in the task amounts to avoid “response-set” like responding. Finally, there are realistic magnitude differences in the practical amounts of the nonmonetary outcomes. That is, \$500 would have been a very large amount of food and \$100 of health would not be very much (in the US system at least), and thus finding a single value that was a practical amount of the nonmonetary outcomes was not possible. Future research should consider, a priori, the comparisons of most interest and select magnitudes and outcomes accordingly.

In addition to the differences in delay discounting across participants based on nicotine use, we can also examine differences in delay discounting across the outcomes. Previous research has found consumable outcomes, such as food, alcohol, and entertainment, are discounted more steeply than money across participants, regardless of nicotine use (e.g., Baker et al., 2003; Friedel et al., 2014; Odum & Rainaud, 2003). We replicated this finding in the present study, showing that all groups discounted consumable outcomes more steeply than money. However, our results with monetary gains and losses, as well as health outcomes, are more complex. Although previous research has shown that monetary losses are discounted less steeply than gains (e.g., Friedel et al., 2016; Johnson et al., 2007; Ohmura et al., 2005), we were unable to detect that difference in the present study. However, this finding may be due to the magnitude of the gain–loss comparison (\$500 instead of \$100). Larger quantities are discounted less than small quantities (Baker et al., 2003) and comparing \$500 gains and losses may have reduced previously reported differential discounting of gains and losses. Conversely, a \$100 loss condition may have provided a better comparison to replicate previous research on gain–loss asymmetry. A \$100 loss condition would have also allowed us to investigate the magnitude effect in losses. In addition, previous research has shown that a temporary health boost is discounted less steeply than a temporary health cure (Friedel et

al., 2016), but we detected no difference. Lastly, our results suggest that monetary losses are discounted less steeply than a temporary health cure, but previous research found no difference (Friedel et al., 2016). Future research should be conducted to examine these outcomes more closely, perhaps with a larger sample size.

Finally, the degree of discounting for 90% of the pairwise combinations of outcomes were significantly correlated, and all correlations were positive. This finding replicates previous work (e.g., Friedel et al., 2016; see Odum et al., 2020) demonstrating that how an individual discounts one outcome is predictive of how they discount other outcomes. Our results further support the assertion that delay discounting has trait-like qualities (Odum, 2011b) and is a transdiagnostic process (Bickel et al., 2019) that underlies many maladaptive behaviors.

Our results support delay discounting as a behavioral marker of addiction. Nicotine consumption of any kind was associated with a higher degree of delay discounting (e.g., impulsivity) compared to non-tobacco users. There were also indications of trait-like characteristics of discounting. Specifically, discounting of any given outcome was positively correlated with the discounting of the other outcomes. Combined with the elevated delay discounting of tobacco users, our results support delay discounting as a key behavioral process for understanding addiction and other maladaptive behaviors. In addition, adoption of tobacco products that have been perceived as less harmful (e.g., e-cigarettes) was not associated with a lower degree of delay discounting when adopted after a history of cigarette use.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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References

- Amlung M, Vedelago L, Acker J, Balodis I, & MacKillop J. (2017). Steep delay discounting and addictive behavior: A meta-analysis of continuous associations. *Addiction*, 112, 51–62. 10.1111/add.13535
- Audrain-McGovern J, Rodriguez D, Epstein LH, Cuevas J, Rodgers K, & Wileyto EP (2009). Does delay discounting play an etiological role in smoking or is it a consequence of smoking? *Drug and Alcohol Dependence*, 103, 99–106. 10.1016/j.drugalcdep.2008.12.019 [PubMed: 19443136]
- Baker F, Johnson MW, & Bickel WK (2003). Delay discounting in current and never-before cigarette smokers: Similarities and differences across commodity, sign, and magnitude. *Journal of Abnormal Psychology*, 112, 382–392. [PubMed: 12943017]

- Bialaszek W, Marcowski P, & Cox DJ (2017). Differences in delay, but not probability discounting, in current smokers, e-cigarette users, and never smokers. *The Psychological Record*, 67, 223–230. 10.1007/s40732-017-0244-1 [PubMed: 28546648]
- Bickel WK, Athamneh LN, Basso JC, Mellis AM, DeHart WB, Craft WH, & Pope D. (2019). Excessive discounting of delayed reinforcers as a transdiagnostic process: Update on the state of the science. *Current Opinion in Psychology*, 30, 59–64. 10.1016/j.copsyc.2019.01.005 [PubMed: 30852411]
- Bickel WK, Odum AL, & Madden GJ (1999). Impulsivity and cigarette smoking: Delay discounting in current, never, and ex-smokers. *Psychopharmacology*, 146, 447–454. [PubMed: 10550495]
- Bedford Scientific Ltd., (n.d.). Micro+ smokerlyzer operating manual. www.bedfont.com.
- CDC (2017). QuickStats: Number of deaths from 10 leading causes by Sex - National Vital Statistics System, United States, 2015. *Morbidity and Mortality Weekly Report*, 66, 413. [PubMed: 28426642]
- CDC, Office on Smoking and Health (2018). Map of current cigarette use among adults. Retrieved from <https://www.cdc.gov/statesystem/cigaretteuseadult.html>
- Cheng YC, Rostron BL, Day HR, Stanton CA, Hull LC, Persoskie A, Travers MJ, Taylor K, Conway KP, Ambrose BK, & Borek N. (2017). Patterns of use of smokeless tobacco in US adults, 2013–2014. *American Journal of Public Health*, 107(9), 1508–1514. 10.2105/AJPH.2017.303921 [PubMed: 28727534]
- Cohen J. (1992). A power primer. *Psychological Bulletin*, 112, 155–159. [PubMed: 19565683]
- Daugherty JR, & Brase GL (2010). Taking time to be healthy: Predicting health behaviors with delay discounting and time perspective. *Personality and Individual Differences*, 48, 202–207. 10.1016/j.paid.2009.10.007
- Du W, Green L, & Myerson J. (2002). Cross-cultural comparisons of discounting delayed and probabilistic rewards. *The Psychological Record*, 52, 479–492. 10.1007/BF03395199
- Ferguson CJ, & Heene M. (2012). A vast graveyard of undead theories: Publication bias and psychological science's aversion to the null. *Perspectives on Psychological Science*, 7(6), 555–561. 10.1177/1745691612459059 [PubMed: 26168112]
- Friedel JE, DeHart WB, Foreman AM, & Andrew ME (2019). A Monte Carlo method for comparing generalized estimating equations to conventional statistical techniques for discounting data. *Journal of the Experimental Analysis of Behavior*, 111, 207–224. 10.1002/jeab.497 [PubMed: 30677137]
- Friedel JE, DeHart WB, Frye CCJ, Rung JM, & Odum AL (2016). Discounting of qualitatively different delayed health outcomes in current and never smokers. *Experimental and Clinical Psychopharmacology*, 24, 18–29. 10.1037/pha0000062 [PubMed: 26691848]
- Friedel JE, DeHart WB, Madden GJ, & Odum AL (2014). Impulsivity and cigarette smoking: Discounting of monetary and consumable outcomes in current and non-smokers. *Psychopharmacology*, 231, 4517–4526. 10.1007/s00213-014-3597-z [PubMed: 24819731]
- Frye CCJ, Galizio A, Friedel JE, DeHart WB, & Odum AL (2015). Measuring delay discounting in humans using an adjusting amount task. *Journal of Visual Experiments*, 107, e53584. 10.3791/53584
- Gonzalez-Roz A, Secades-Villa R, Pericot-Valverde I, Weidberg S, & Alonso-Perez F. (2019). Effects of delay discounting and other predictors on smoking relapse. *The Spanish Journal of Psychology*, 22, E9. 10.1017/sjp.2019.11. [PubMed: 30885283]
- Hanley JA, Negassa A, Edwards MDD, & Forrester JE (2003). Statistical analysis of correlated data using generalized estimating equations: An orientation. *American Journal of Epidemiology*, 157, 364–375. 10.1093/aje/kwf215 [PubMed: 12578807]
- Johnson MW, & Bickel WK (2008). An algorithm for identifying nonsystematic delay-discounting data. *Experimental and Clinical Psychopharmacology*, 16, 264–274. 10.1037/1064-1297.16.3.264 [PubMed: 18540786]
- Johnson MW, Bickel WK, & Baker F. (2007). Moderate drug use and delay discounting: A comparison of heavy, light, and never smokers. *Experimental and Clinical Psychopharmacology*, 15, 187–194. 10.1037/1064-1297.15.2.187 [PubMed: 17469942]

- Karakula SL, Weiss RD, Griffin ML, Borges AM, Bailey AJ, & McHugh RK (2016). Delay discounting in opioid use disorder: Differences between heroin and prescription opioid users. *Drug and Alcohol Dependence*, 169, 68–72. 10.1016/j.drugalcdep.2016.10.009 [PubMed: 27776247]
- Lesieur HR, & Blume SB (1987). The South Oaks Gambling Screen (SOGS): A new instrument for the identification of pathological gamblers. *American Journal of Psychiatry*, 144, 1184–1188. 10.1176/ajp.144.9.1184
- MacKillop J, Amlung MT, Few LR, Ray LA, Sweet LH, & Munafò MR (2011). Delayed reward discounting and addictive behavior: A meta-analysis. *Psychopharmacology*, 216, 305–321. 10.1007/s00213-011-2229-0 [PubMed: 21373791]
- Madden GJ, Petry NM, Badger GJ, & Bickel WK (1997). Impulsive and self-control choices in opioid-dependent patients and non-drug-using control patients: Drug and monetary rewards. *Experimental and Clinical Psychopharmacology*, 5, 256. 10.1037//1064-1297.5.3.256 [PubMed: 9260073]
- McMillen RC, Gottlieb MA, Shaefer RMW, Winickoff JP, & Klein JD (2014). Trends in electronic cigarette use among US adults: Use is increasing in both smokers and nonsmokers. *Nicotine and Tobacco Research*, 17, 1195–1202. 10.1093/ntr/ntu213 [PubMed: 25381306]
- Mitchell SH (2004). Measuring impulsivity and modeling its association with cigarette smoking. *Behavioral and Cognitive Neuroscience Reviews*, 3, 261–275. 10.1177/1534582305276838 [PubMed: 15812110]
- Mokdad AH, Marks JS, Stroup DF, & Gerberding JL (2005). Correction: actual causes of death in the United States, 2000. *Journal of the American Medical Association*, 293, 293–294. 10.1001/jama.293.3.293 [PubMed: 15657315]
- Moon GW, & Gorsuch RL (1988). Information Inventory: The quicker quick test of intelligence. *Journal of Clinical Psychology*, 44, 248–251. 10.1002/1097-4679 [PubMed: 3360942]
- Odum AL (2011a). Delay discounting: I'm a k, you're a k. *Journal of the Experimental Analysis of Behavior*, 96, 427–439. 10.1901/jeab.2011.96-423 [PubMed: 22084499]
- Odum AL (2011b). Delay discounting: Trait variable? *Behavioral Processes*, 87, 1–9. 10.1016/j.beproc.2011.02.007
- Odum AL, Baumann AA, & Rimington DD (2006). Discounting of delayed hypothetical money and food: Effects of amount. *Behavioral Processes*, 73, 278–284. 10.1016/j.beproc.2006.06.008
- Odum AL, Becker RJ, Haynes JM, Galizio A, Frye C, Downey H, Friedel JE, & Perez DM (2020). Delay discounting of different outcomes: Review and theory. *Journal of the Experimental Analysis of Behavior*, 113(3), 657–679. 10.1002/jeab.589. [PubMed: 32147840]
- Odum AL, Madden GJ, & Bickel WK (2002). Discounting of delayed health gains and losses by current never- and ex-smokers of cigarettes. *Nicotine and Tobacco Research*, 4, 295–303. 10.1080/14622200210141257 [PubMed: 12215238]
- Odum AL, & Rainaud CP (2003). Discounting of delayed hypothetical money, alcohol, and food. *Behavioural Processes*, 64, 305–313. 10.1016/S0376-6357(03)00145-1 [PubMed: 14580700]
- Ohmura Y, Takahashi T, & Kitamura N. (2005). Discounting delayed and probabilistic monetary gains and losses by smokers of cigarettes. *Psychopharmacology*, 182, 508–515. 10.1007/978-4-431-55402-8_8 [PubMed: 16167142]
- Oncken C, McKee S, Krishnan-Sarin S, O'Malley S, & Mazure CM (2005). Knowledge and perceived risk of smoking-related conditions: A survey of cigarette smokers. *Preventative Medicine*, 40, 779–784. 10.1016/j.ypmed.2004.09.024
- Open Science Collaboration (2015). PSYCHOLOGY. Estimating the reproducibility of psychological science. *Science*, 349(6251), aac4716. 10.1126/science.aac4716
- Saunders JB, Aasland OG, Babor TF, De la Fuente JR, & Grant M. (1993). Development of the Alcohol Use Disorders Identification Test (AUDIT): WHO collaborative project on early detection of persons with harmful alcohol consumption. *Addiction*, 88, 791–804. 10.1111/j.1360-0443.1993.tb02093.x [PubMed: 8329970]
- Sheffer CE, Miller A, Bickel WK, Devonish JA, O'Connor RJ, Wang C, Rivard C, & Gage-Bouchard EA (2018). The treasure of now and an uncertain future: Delay discounting and health behaviors among cancer survivors. *Cancer*, 124, 4711–4719. 10.1002/cncr.31759 [PubMed: 30343494]

- Shrout PE, & Rodgers JL (2018). Psychology, science, and knowledge construction: Broadening perspectives from the replication crisis. *Annual Review of Psychology*, 69, 487–510. 10.1146/annurev-psych-122216-011845
- Snider SE, DeHart WB, Epstein LH, & Bickel WK (2019). Does delay discounting predict maladaptive health and financial behaviors in smokers? *Health Psychology*, 38, 21–28. 10.1037/hea0000695 [PubMed: 30474996]
- Strickland JC, Alcorn JL 3rd, & Stoops WW (2019). Using behavioral economic variables to predict future alcohol use in a crowdsourced sample. *Psychopharmacology*, 33(7), 779–790. 10.1177/0269881119827800
- Sung HY, Wang Y, Yao T, Lightwood J, & Max W. (2016). Poly tobacco use of cigarettes, cigars, chewing tobacco, and snuff among US adults. *Nicotine and Tobacco Research*, 18, 817–826. 10.1093/ntr/ntv147. [PubMed: 26136525]
- Sweitzer MM, Donny EC, Dierker LC, Flory JD, & Manuck SB (2008). Delay discounting and smoking: Association with the Fagerström Test for Nicotine Dependence but not cigarettes smoked per day. *Nicotine and Tobacco Research*, 10, 1571–1575. 10.1080/14622200802323274. [PubMed: 18946776]
- Weidberg S, González-Roz A, Martínez-Loredo V, López-Núñez C, Pericot-Valverde I, & Secades-Villa R. (2017). Delay discounting among smokers, e-cigarette users and non-dependent controls. *Drug and Alcohol Dependence*, 171, e214. 10.1016/j.drugalcdep.2016.08.585
- Weidberg S, González-Roz A, & Secades-Villa R. (2017). Delay discounting in e-cigarette users, current and former smokers. *International Journal of Clinical and Health Psychology*, 17, 20–27. 10.1016/j.ijchp.2016.07.004 [PubMed: 30487877]
- Wingen T, Berkessel JB, & Englich B. (2020). No replication, no trust? How low replicability influences trust in psychology. *Social Psychological and Personality Science*, 11(4), 454–463. 10.1177/1948550619877412

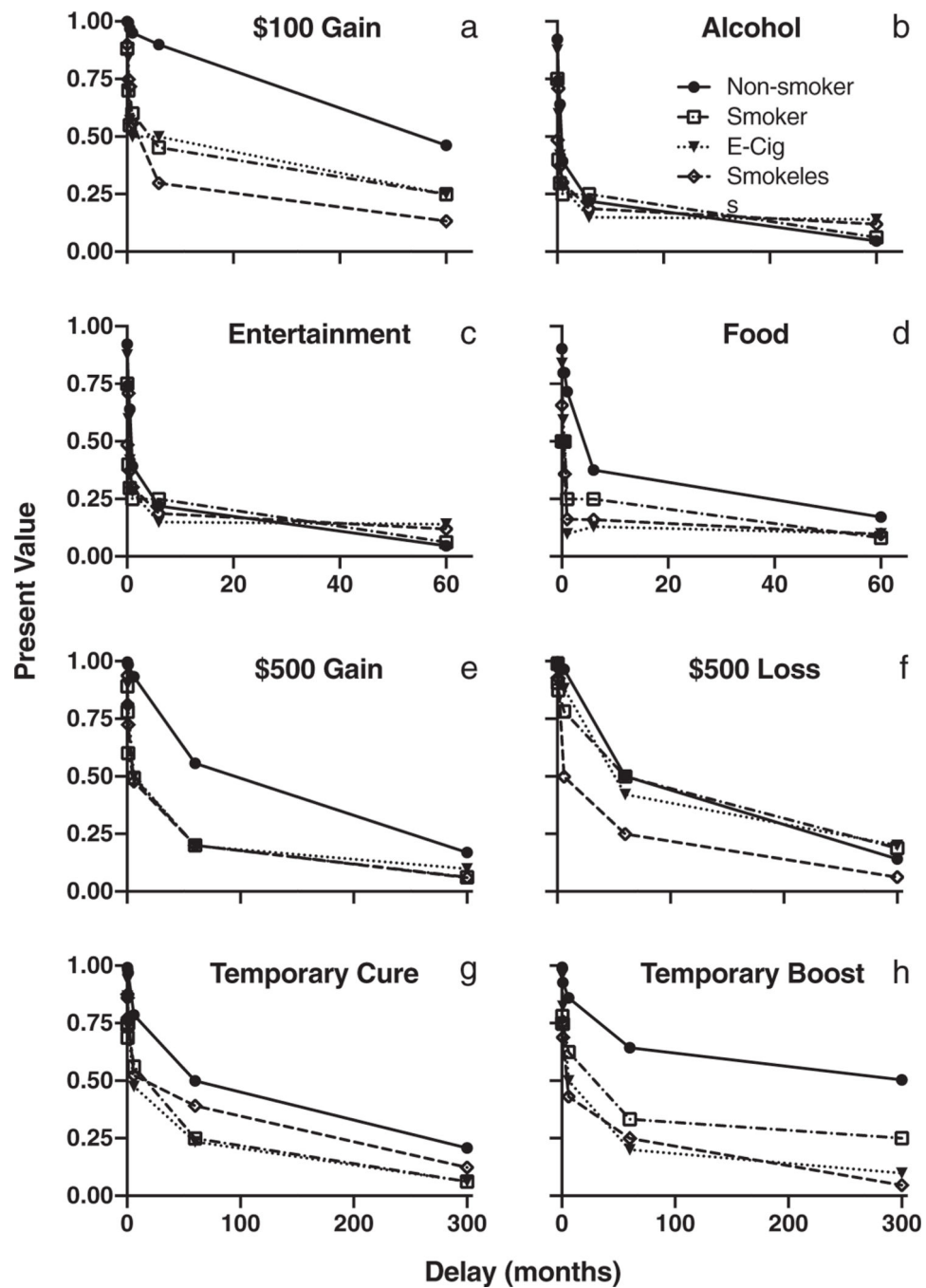


Figure 1.
Median Indifference Points for Each Group by Outcome Connected by Straight Lines

Table 1

Participant Demographics

	Tobacco usage				Significant
	Non-user	Smoker	Smokeless	E-Cigarette	
n	30	37	20	15	
White	90%	81%	85%	100%	
Male	77%	64%	70%	86%	
Age	37.10 (12.84)	39.41 (12.84)	38.45 (11.70)	25.13 (6.79)	***
Education ^a	3.33 (1.40)	2.57 (1.37)	2.90 (1.86)	2.60 (1.64)	
Monthly Income (\$)	1842.67 (1540.07)	1481.54 (2059.16)	1412.75 (964.93)	1706.00 (837.92)	
II	104.33 (15.88)	97.32 (14.39)	99.25 (16.80)	100.06 (11.32)	
SOGS	1.23 (3.56)	1.41 (2.40)	2.10 (3.99)	1.93 (3.99)	
EDS	17.03 (7.14)	17.62 (7.68)	16.15 (9.02)	13.33 (5.12)	
AUDIT	5.63 (3.87)	9.78 (7.48)	9.1 (7.16)	5.53 (3.50)	*
FTND	-	4.73 (2.18)	-	5.47 (2.20)	
CO (ppm) ^b	1.77 (0.86)	11.19 (4.14)	5.00 (5.62)	4.07 (8.05)	***

Note. II = Information Inventory, SOGS = South Oaks Gambling Screen, EDS = Eating Disturbance Scale, AUDIT = Alcohol Use Disorders Identification Test, FTND = Fagerström Test of Nicotine Dependence. Differences in demographics across groups was assessed with ANOVAs. For differences in FTND scores, a *t*-test was used.

* $p < .05$,

** $p < .01$,

*** $p < .001$.

^a Participants were asked about their highest level of obtained education.

^b A carbon monoxide reading was not recorded for one e-cigarette user.

Table 2

Differences in Mean Adjusted-Indifference Points by Group

	Mean Difference		
	Non-user	E-Cigarette User	Smokeless Tobacco User
Cigarette Smoker	0.14 *	−0.01	−0.00 ^a
Smokeless Tobacco User	0.15 *	−0.00 ^a	
E-Cigarette User	0.15 *		

^aDifferences between the groups rounded to zero but were negative values.

*
 $p < .05$,

**
 $p < .01$,

 $p < .001$,

p -values were corrected with the Benjamini-Hochberg procedure to have a constant false discovery rate. All values are the mean adjusted-indifference point of the column minus the mean adjusted-indifference point of the row.

Table 3

Differences in Mean Adjusted-Indifference Points by Outcome Type

	Mean Difference		
	\$100 Gain	Food	Entertainment
Alcohol	0.18 ***	-0.01	-0.01
Entertainment	0.16 ***	-0.03	
Food	0.19 ***		
	\$500 Gain	Cure	Boost
\$500 Loss	-0.05	-0.09 *	-0.07
Boost	0.01	-0.03	
Cure	0.04		
	\$100 Gain		
\$500 gain	-0.17 ***		

*
 $p < .05$,**
 $p < .01$,***
 $p < .001$,

p -values were corrected with the Benjamini-Hochberg procedure to have a constant false discovery rate. All values are the mean adjusted-indifference point of the column minus the mean adjusted-indifference point of the row.

Table 4

Differences in Mean Adjusted-Indifference Points between Nicotine Non-Users and Users

Outcome Type	Mean Difference	Sig.
\$100 Gain	0.158	*
Alcohol	0.060	-
Entertainment	0.186	*
Food	0.172	*
\$500 Gain	0.155	**
\$500 Loss	0.099	-
Boost	0.245	***
Cure	0.154	**

*
 $p < .05$,

**
 $p < .01$,

 $p < .001$,

p -values were corrected with the Benjamini-Hochberg procedure to have a constant false discovery rate. All values are the mean indifference point for the non-users minus the mean indifference point for the nicotine users.

Table 5

Pearson Correlations (R) of Mean Indifference Points Between Each Outcome Pair

	\$100 Gain	Alcohol	Ent.	Food	\$500 Gain	\$500 Loss	Temp. Cure
Alcohol	0.40***	-					
Ent.	0.53***	0.19	-				
Food	0.43***	0.40***	0.45***	-			
\$500 Gain	0.83***	0.35***	0.48***	0.46***	-		
\$500 Loss	0.39***	0.27**	0.14	0.31**	0.54***	-	
Temp. Cure	0.42***	0.22*	0.48***	0.38***	0.51***	0.29**	-
Temp. Boost	0.37***	0.29**	0.44***	0.41***	0.39***	0.14	0.54***

**

p < .01,

p < .001