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Bleak Present, Bright Future: II. Combined Effects of Episodic Future Thinking and Scarcity on Delay Discounting in Adults at Risk for Type 2 Diabetes

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Abstract

The present study sought to determine if episodic future thinking (EFT) can decrease delay discounting (DD) and demand for fast food under simulations of economic scarcity in adults at risk for diabetes (i.e., overweight/obese and with hemoglobin A1c values in, or approaching, the prediabetic range). Across two sessions, participants completed assessments of DD and food demand at baseline and while prompted to: 1) engage in either EFT or control episodic recent thinking (ERT), and 2) while reading a brief narrative describing either economic scarcity or neutral income conditions. Results showed that EFT significantly reduced DD, whereas the economic scarcity narrative significantly increased DD; no significant interaction between EFT and scarcity was observed. No significant effect of either EFT or scarcity was observed on food demand. We conclude that EFT decreases DD even when challenged by simulated economic scarcity in adults at risk for diabetes. The absence of a significant interaction between EFT and scarcity suggests that these variables operate independently to influence DD in opposing

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Author Contributions: WKB, LHE, and JSS designed the experiment. All authors assisted in the conduct of the experiment. JSS and RAP performed data analyses. JSS drafted the manuscript, with feedback from all authors. All authors read and approved the final manuscript.

Conflict of Interest: Although the following activities/relationships do not create conflict of interests pertaining to this manuscript, in the interest of full disclosure, we would like to report the following: Warren K. Bickel is a principal of HealthSim, LLC; Notifius, LLC; BEAM Diagnostics, Inc.; and a partner for Red 5 Group, LLC. In addition, he serves on the scientific advisory board for Sober Grid, Inc.; Ria Health; US WorldMeds, LLC; and is a consultant for Alkermes, Inc. and Nektar Therapeutics. Dr. Mastrandrea received research funding from the Juvenile Diabetes Research Foundation, NovoNordisk, Sanofi Aventis, and AstraZeneca. The other authors do not declare any conflict of interest with respect to the authorship or publication of this article.

Ethics Approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all individual participants included in the study and all study procedures were approved by the University at Buffalo Institutional Review Boards.

directions. Effects of EFT and economic scarcity on food demand require further study. The present study was registered on clinicaltrials.gov (NCT03664726).

Keywords

Delay discounting; episodic future thinking; scarcity; income shock; prediabetes; obesity

Type 2 diabetes is a leading cause of morbidity and mortality both globally and nationally (Heron, 2018). Approximately 30.3 million Americans alone suffer from this disease (Centers for Disease Control and Prevention, 2017), incurring more than $200 billion annually in direct medical costs and lost productivity (American Diabetes Association, 2013). Behavior plays a prominent role in the etiology of type 2 diabetes (e.g., poor diet, sedentary lifestyle, obesity; Heron, 2018); thus, development of behavioral interventions designed to reduce caloric intake, increase physical activity, and promote weight loss are important for patients at risk for this disease.

Interventions to prevent the progression from prediabetes to type 2 diabetes focus on reducing energy intake, improving diet quality, and increasing physical activity in order to produce weight loss (Perreault et al., 2012). Engaging in these healthy behaviors for their future benefits requires a strong focus on delayed, rather than immediate, outcomes. However, populations at risk for type 2 diabetes show a bias for immediate gratification. Specifically, in cross-sectional studies, prior work has shown that elevated rates of delay discounting (i.e., devaluation of delayed rewards) are robustly associated with diabetes risk factors such as obesity (Amlung et al., 2016; Epstein et al., 2014; Epstein et al., 2020; Weller et al., 2008), consumption of high energy density food, and sedentary activity (Garza et al., 2016; Snider et al., 2019). Most relevant to the present study, recent data (Epstein et al., 2020) demonstrate that high rates of delay discounting are associated with poorer glycemic control, nonadherence to medications for comorbid conditions, and a variety of other maladaptive health behaviors in patients diagnosed with prediabetes, a condition of elevated blood glucose that is likely to transition to type 2 diabetes in the absence of intervention (Tabak et al., 2012).

Consistent with an experimental medicine approach to behavior change research (Riddle & Science of Behavior Change Working Group, 2015), these prior findings identify delay discounting as a possible therapeutic target in those at risk for diabetes. Specifically, interventions that reduce delay discounting may increase valuation of future health and thus reduce the rate of progression to type 2 diabetes. Subsequent studies demonstrated that an intervention designed to prompt episodic future thinking (EFT; Atance & O'Neill, 2001), in which participants are guided to generate and vividly pre-experience future events during completion of decision-making tasks, successfully reduces delay discounting in overweight and obese populations at risk for diabetes (Mellis, Athamneh, et al., 2018; Stein et al., 2017; Sze et al., 2017). Again, consistent with an experimental medicine approach (Riddle & Science of Behavior Change Working Group, 2015), these and other prior studies (Daniel et al., 2015a, 2013b; Peters & Büchel, 2010; Stein et al., 2016) show that delay discounting is amenable to intervention, suggesting that this decision-making process may be targeted in future clinical trials to reduce the bias for immediate gratification, facilitate weight loss, and improve glycemic control in those at risk for diabetes.

For a behavioral intervention such as EFT to be optimally effective, it should operate under a broad range of conditions, including those that may directly challenge its potential therapeutic effects (e.g., negative income shock). One potential challenge to the therapeutic effects of EFT may be economic scarcity; that is, in experimental research, real or simulated negative income shock (i.e., abrupt transitions to poverty) increases discounting of the future (Bickel et al., 2016; Haushofer et al., 2013; Mellis, Athamneh, et al., 2018; Mellis, Snider, et al., 2018). Only one prior study, however, has examined whether EFT remains effective following negative income shock. Specifically, in overweight and obese participants, Sze et al. (2017) used a between-groups design to investigate the combined effects of EFT and a narrative describing negative income shock. In this prior study, reading the scarcity narrative prior to decision-making tasks increased delay discounting (consistent with prior findings); however, EFT successfully reduced delay discounting in both income shock and control conditions. In this same study, the scarcity narrative increased valuation of high energy density fast foods in a food purchase task, although EFT successfully reduced food valuation in all conditions. Thus, EFT appears to reduce delay discounting and diabetes-relevant behavioral measures even when challenged by simulations of economic scarcity.

The present study sought to extend the findings reported by Sze et al. (2017) by conducting a systematic replication in a laboratory-based sample of participants at even greater risk for diabetes (i.e., who were both overweight/obese *and* had elevated HbA1c). We also sought to increase experimental control by examining these effects using a within-subjects design in which effects of EFT and income narrative were assessed at both baseline and with the interventions. Tests of generality are critical because they may highlight robustness or, alternatively, selectivity of observed effects across diverse populations and contexts. The knowledge gained from these investigations may be used to guide future implementation of interventions like EFT, including adaptations of the intervention to increase efficacy for select populations, if necessary.

Method

Methods

Seventy-eight participants were recruited from two cities in the Southern (n=31) and Northeastern (n=47) United States using physician referral and community advertisements. This sample size provides 95% statistical power to detect a “medium” effect sizes (η_p^2 ≥ .058, converted from Cohen’s *d;* Cohen, 1992) or greater with α=.05 in ANOVA with 2 repeated measures (baseline and intervention) and 4 groups (episodic thinking and income narrative combinations; see below).

To be eligible for the study, participants were required to have a body mass index (BMI) ≥ 25 and have a hemoglobin A1c (HbA1C) level within (5.7–6.4%) or approaching (5.4–5.6%) the prediabetes range. The latter of these HbA1c ranges spans the 0.3% margin of error of study testing devices and, in combination with the overweight/obesity criterion, allowed broader recruitment of patients at risk for diabetes. Additional inclusion criteria required that participants have no prior diagnosis of type 2 diabetes, be over 18 years of age, report no use of glucose altering-medications (e.g., glucocorticoids, metformin, GlP-1 etc), and report no unmanaged psychiatric conditions or substance use disorders.

All participants provided informed consent and procedures were conducted in accordance with guidelines for the ethical conduct of human research outlined by the National Institutes of Health and with Institutional Review Board approval.

Procedures

Session 1—Participants refrained from eating for at least two hours prior to the start of Session 1. To confirm eligibility, participants had their height, weight, and HbA1c measured and completed a number of questionnaires, including a standardized demographic questionnaire (Adler et al., 2000).

Body mass index (kg/m^2) was calculated from weight, measured to the nearest 0.2 lb using a Tanita (Hong Kong, China) digital scale, and height, measured in centimeters to the nearest millimeter using a SECA (Chino, California) stadiometer. HbA1c was measured using the Afinion™ A1c assay (Abbott Diagnostics, Abbott Park, IL) and A1CNow+® system (PTS Diagnostics, Sunnyvale, CA).

Upon confirmation of eligibility, participants were given ten minutes to consume a flavored energy bar (Powerbar, Inc, Glendale, California) in vanilla or chocolate flavor. This served to standardize the amount of food each participant consumed prior to engaging in behavioral tasks. Water was provided ad libitum. Approximately 30 minutes after energy bar consumption, baseline levels of delay discounting were assessed using the adjusting-amount task (Du et al., 2002). In this task participants made repeated hypothetical choices between a larger amount (e.g., $100) delivered after a delay, and a smaller amount delivered immediately. At each of seven delays (1 day, 7 days, 1 month, 3 months, 1 year, 5 years, 25 years; order randomized) the amount of the smaller reward increased or decreased depending on the preceding choice across 6 trials until reaching an indifference amount. At this indifference amount, the subjective value of both rewards is approximately equal. Participants completed two iterations of this task at each of two magnitudes of the larger, delayed reward ($100 and $1000). Two reward magnitudes were chosen in order to provide more comprehensive and accurate measures of discounting, as prior work has demonstrated that rate of delay discounting varies by reward magnitude[25].

Participants then completed a food purchase task (Sze et al., 2017). Participants first selected their preferred fast food from a list of common fast foods (e.g., McDonald’s hamburgers, Taco Bell tacos). Participants were then asked to report the number of servings they would purchase across a range of ascending prices ($0.00, $0.06, $0.12, $0.25, $0.50, $1.00, $2.00, $5.00, $10.00, $20.00, $40.00, $80.00). Participants were asked to assume: (1) that they could not save or stockpile food for a later date; (2) that they had no other access to their chosen food, but could purchase and eat other foods as they normally would; (3) that the available serving sizes were a single unit of each food item (e.g., one taco, one hamburger, etc.); (4) that they could not give away or share any of the purchased food; and (5) that they had the same income/savings they did now.

Session 2—Participants again refrained from eating for at least 2 hours before the start of Session 2. Upon arrival, participants consumed an energy bar as in Session 1 and were then assigned to either EFT or episodic "recent" thinking (ERT) control groups, and either scarcity narrative or neutral income control groups, using block randomization stratified by site (UB/VT), gender, and education. Episodic thinking and income narrative were between-subjects manipulations to avoid possible order effects between conditions.

To generate episodic events participants used a self-guided generation task similar to those administered in prior studies. EFT participants generated seven personalized future events that they were looking forward to and could vividly imagine at different time frames (1 day, 7 days, 1 month, 3 months, 1 year, 5 years, 25 years). ERT participants generated seven personalized recent past events that they enjoyed and could vividly remember at different time frames in the recent past (1, 2, 3, 4, 5, 6, and 7 days ago). This ERT condition, used frequently in prior research (Daniel et al., 2015b; Lin & Epstein, 2014; O'Donnell et al., 2017; O'Neill et al., 2016; Snider et al., 2017; Snider, LaConte, Bickel, 2016; Stein et al., 2017, 2016; Sze et al., 2017), isolates the effects of prospection in EFT by ensuring that episodic thinking in both groups engages memory, features personalized details, and is matched for vividness. All participants were instructed to imagine and describe events that were positive, vivid, specific, and could occur over the time frame specified. Participants were further prompted to imagine experiencing this event and asked to describe details including who was present, what they were doing, where they were, and how they were feeling. Detailed and positive event description examples, along with vague and negative examples were provided and labeled as "good" and "bad" to emphasize the importance of positivity, specificity, and vividness. In addition, a checklist of task requirements (i.e., positivity, vividness, specificity) was provided at the end of each event generation to use as a reference.

Next, participants were presented with their assigned income narrative (scarcity or neutral) and asked to read it out loud and consider it for at least 15 seconds. Narratives remained on the screen for 30 seconds before participants could continue to allow time for both reading and consideration. Participants were asked to assume they were actually experiencing the conditions described in each narrative. The scarcity and neutral narratives read, as follows (Bickel et al., 2016):

> Scarcity: *You have just been fired from your job. You will now have to move in with a relative who lives in a part of the country you dislike, and you will have to spend all of your savings to move there. You do not qualify for unemployment, so you will not be making any income until you find another job.*
>
> Neutral: *At your job, you have just been transferred to a different department in a location across town. It is a similar distance from where you live so you will not have to move. You will be making 2% more than you previously were.*

Participants then completed the same adjusting-amount tasks completed in Session 1, although participants were now asked to vividly imagine their EFT or ERT events and scarcity or neutral income narrative during the task. Scarcity or neutral income narratives were again presented on the screen prior to each new delay block. At each question, self-generated text descriptions of EFT or ERT events were presented on the screen, with the time frame of the event corresponding to the delay (e.g., most proximal events paired with the shortest delay).

Finally, participants completed the same food purchase task completed in Session 1, but were prompted to read and consider their assigned income narrative prior to the start of the task and imagine their episodic events during each question, as described for the delay discounting task. Consistent with the prior study on the combined effects of EFT and scarcity (Sze et al., 2017), only the one-year EFT event or its corresponding ERT time frame (five days) were presented.

Data analysis

Demographic measures—Baseline comparisons of continuous demographic variables and discounting by groups were performed using analysis of variance (ANOVA). Group differences in sex, minority status, site, diagnoses, and medication classifications were assessed using Pearson's Chi-square test.

Delay discounting—We applied standardized diagnostic criteria to data from the adjusting-amount delay discounting task to detect the possible presence of data that were not systematically affected by delay. Such data, if present, may be the product of inattention to the task or failure to understand task instructions. Briefly, Johnson and Bickel (2008) outlined two criteria to identify nonsystematic discounting data. Criterion 1 assumes consistent local effects of contiguous delays, with no or few increments in delay containing an increase in discounted value. Criterion 2 assumes a decreasing trend in discounted value across delays, wherein the magnitude of the reduction in value from the first to last delay should equal at least 10% of the objective (undiscounted) value of the large reward. All participants' data at baseline met these criteria in at least one of two reward magnitudes and were thus included in analysis.

Area under the curve (AUC) for each participants' discounting functions served as our dependent measure of delay discounting. Higher measures of AUC indicate lower levels of discounting. AUC, which ranges from 0 (maximum discounting of the delayed reward) to 1 (no discounting) is an atheoretical measure which does not rely on *a priori* assumptions about the shape of the discounting function (Myerson et al., 2001) (e.g., hyperbolic), which may be altered by the presence of EFT or scarcity narratives. We calculated AUC using the ordinal values for each of the seven delays (1 day through 25 years). This measure of AUC calculated from ordinal transformation of delay values (AUC_{ord}; Borges et al., 2016) was chosen over the traditional AUC measure because it does not overweight the contribution of distal delays. That is, delays in the delay discounting task are pseudo-logarithmically distributed; thus, the intervals between longer delays contribute to the traditional AUC measure proportionally more than those from shorter delays. Scaling delays ordinally ensures that the contribution from each delay interval contributes equally to AUC. Prior work has shown that AUC_{ord}, or similar methods (i.e., AUC calculated from logarithmic transformation of delays; Yoon et al., 2017), yields measures that are highly correlated (inversely) with standard measures of discount rate, *k,* from a hyperbolic discounting model (Mazur, 1987).

Change in delay discounting (AUC_{ord}; Session 2-Session 1) was analyzed using 2 × 2 × 2 ANCOVA, with episodic thinking (EFT, ERT) and income narrative (scarcity, neutral) between-subjects variables and magnitude ($100, $1000) as a within-subjects factor. We examined all possible two- and three-way interactions between factors. AUC_{ord} change scores were analyzed with baseline AUC_{ord} values as covariates (Crager, 1987; Frison & Pocock, 1992; Senn, 1989) to improve efficiency of the analysis and to remove the influence of chance imbalance in baseline levels of the outcome measure.

Food purchase task—First, we applied standardized diagnostic criteria (Stein et al., 2015) to detect possible instances in which purchasing was not systematically affected by price (e.g., invariant or inconsistent purchasing across price). Such data may reflect inattention to the task or failure to understand task instructions. Participants whose baseline data failed to meet these criteria ($n = 3$) were included in primary analyses and excluded in secondary analyses (see below). In addition, two participants' had missing baseline purchase task data; thus, these participants were excluded from all analyses.

Demand functions for each participant were then fitted using an exponential demand model (Koffarnus et al., 2015):

$$Q = Q_0 * 10^{k\left(e^{-\alpha Q_0 P} - 1\right)} \quad (1)$$

in which Q is quantity purchased, P is price, k is the span of purchased values in $\log_{10}$ units, and the free parameters Q_0 and α provide estimates of *the intensity of demand* (consumption unconstrained by price) and *elasticity of demand* (sensitivity to price), respectively. Greater intensity of demand and lower elasticity of demand represent greater valuation of the commodity under investigation. All curve fitting was performed in GraphPad Prism (ver. 7.0, La Jolla, CA, USA). Median R^2 values were .93 and .91 in Sessions 1 and 2, respectively. Demand measures were non-normally distributed and were, thus, log-transformed prior to analysis. Group differences were examined using ANOVA, as for delay discounting. A sensitivity analysis was performed to retest the main hypothesis in an additional model in which nonsystematic purchase task data ($n = 3$; Stein et al., 2015) were included.

All inferential statistical analyses described above were carried out in SPSS v 26.

Results

Participant characteristics

Demographic and other characteristics for participants in the EFT and ERT groups are displayed in Table 1. No differences were observed by group in any of the baseline (Session 1) measures, including baseline delay discounting (in all cases, $p > .07$).

Delay discounting

Figure 1 displays AUC_{ord} change scores between Sessions 1 (no cues/narratives) and 2 (with EFT cues and income shock narratives) for all participants. We observed a significant main effect of episodic thinking, $F(1, 72) = 4.082$, $p = .047$, $\eta_p^2 = .054$ (higher AUC_{ord}, or less discounting, in the EFT groups in Session 2), and Income Narrative, $F(1, 72) = 16.246$, $p < .001$, $\eta_p^2 = .184$ (lower AUC_{ord} in the scarcity groups in Session 2). The main effect of magnitude on change scores was not significant, $F(1, 74) = 0.114$, $p = .737$, $\eta_p^2 = .002$. Moreover, no significant two- or three-way interactions were observed between episodic thinking, income narrative, and magnitude (in all cases, $F < 2.218$, $p > .140$, $\eta_p^2 < .030$). Notably, the Episodic Thinking x Income Narrative interaction was not significant, $F(1, 74) = 0.003$, $p = .956$, $\eta_p^2 = .000$, indicating that the effects of EFT and scarcity on delay discounting were independent of each other.

Food purchase task

Figure 2 displays change scores between Sessions 1 and 2. Including all participants in the analysis, we observed no significant main effects of episodic thinking or income narrative, or interactions, on either demand intensity (in all cases, $F < 0.204$, $p > .653$, $\eta_p^2 < .004$) or demand elasticity (in all cases, $F < 3.162$, $p > .079$, $\eta_p^2 < .044$). Sensitivity analysis excluding nonsystematic purchasing data included ($n = 3$) yielded identical conclusions.

Discussion

Prior studies have identified delay discounting as a potential therapeutic target in those at risk for diabetes (Epstein et al., 2020) and have successfully reduced delay discounting in those at risk for type 2 diabetes (Daniel et al., 2013b; Stein et al., 2017; Sze et al., 2017) using EFT. In the present laboratory-based study, we sought to extend findings from a prior online study (Sze et al., 2017) to determine if EFT mitigates the counter-therapeutic effects of economic scarcity on delay discounting and measures of food demand in adults at risk for diabetes (i.e., overweight/obese and with elevated HbA1c). Consistent with the findings of Sze et al., results indicated that EFT decreased delay discounting and that the economic scarcity narrative increased delay discounting. However, inconsistent with prior findings, neither EFT nor economic scarcity significantly influenced measures of food demand.

Delay Discounting

Effects of EFT on delay discounting in the present study are generally consistent with prior reports of EFT's effects in diverse clinical populations (Daniel et al., 2013b; Peters & Büchel, 2010; Snider et al., 2016; Stein et al., 2017, 2016). Moreover, results of this study showed that EFT operates similarly under economic scarcity and neutral income conditions, consistent with prior online findings in overweight and obese participants (Sze et al., 2017). That is, EFT produced therapeutic effects on delay discounting regardless of whether participants were exposed to economic scarcity or neutral conditions. This represents an important test of the efficacy of EFT for reducing delay discounting, as the clinical utility of an intervention is influenced by its ability to operate under a diverse range of conditions. The present study's use of an in-person, laboratory-based sample provides further confirmation of previously observed findings and extends these findings to a more clinically advanced population; that is, adults with prediabetes or with elevated A1c values, a condition in which discounting of future outcomes may influence transition to type 2 diabetes (Epstein et al., 2019).

Fast Food Demand

The prior online study of combined EFT and scarcity in overweight and obese participants showed that EFT significantly decreased behavioral economic demand for fast food in a hypothetical purchase task; conversely, economic scarcity increased demand. However, the present study revealed no significant effect of either EFT or scarcity on demand measures, despite using the same food purchase task. These discrepant findings may be due to one or more differences in populations between studies. Compared to the general sample of overweight and obese participants examined by Sze et al. (2017), participants in the present sample had to meet criteria for elevated HbA1c, the majority of whom had diagnoses of prediabetes. In addition, numerous other differences were observed between the samples in the present study and Sze et al., including BMI (mean: 37.77 and 33.47, respectively), age (mean: 50.33 and 37.93, respectively), and percentage of female participants (78.21% and 52%, respectively). Future studies should examine a possible moderating role of each of these variables in the effects of EFT and scarcity on food demand. Here, we note that elevated HbA1c levels may have been particularly important. Specifically, central insulin regulates the reinforcing value of food through modulation of mesolimbic reward circuitry, with insulin resistance (as is common in prediabetes) associated with *increased* food reinforcement (Figlewicz, 2003; Figlewicz & Benoit, 2009; Figlewicz et al., 2006; Tiedemann et al., 2017). Thus, valuation of high energy density fast foods in participants with prediabetes or elevated HbA1c may be more resistant to the effects of interventions, including EFT, than the general sample of overweight and obese participants examined previously (Sze et al., 2017).

We note also that recruitment of 78 participants in the present study yielded 95% power to detect a “medium” effect size or greater, which is consistent with the “medium” to “large” effect sizes of EFT on fast food demand observed by Sze et al. However, if one or more of the observed sample differences (e.g., HbA1c, BMI, gender) made food reinforcement more resistant to intervention in this study, this may serve to diminish the effect size of EFT on food demand. Indeed, the observed (nonsignificant) effect size on demand elasticity in the present study was in the small range (e.g., main effect of EFT on demand elasticity: $\eta_p^2 = .043$, $p = .080$). Thus, implementation of EFT in future studies may require larger samples to detect significant effects. Alternatively, future studies could investigate adaptations of EFT in order to increase efficacy. Toward this end, longer exposure to EFT prior to testing may hold promise, as recent data suggest that the behavioral effects of EFT increase cumulatively over time (Mellis, Snider, Deshpande, LaConte, & Bickel, 2020). Regardless, null effects on food demand in the present systematic replication highlight the need for more thorough investigation of potential moderating variables in future studies.

Implications and Future Directions

Consistent with an experimental medicine approach to behavior change (Riddle & Science of Behavior Change Working Group, 2015), the effects of EFT on delay discounting in the present study show that delay discounting is a potential therapeutic target in the prevention of type 2 diabetes that is amenable to change with targeted intervention. This suggests that EFT may be used as a clinical intervention to increase valuation of the future, facilitate weight loss, and improve glycemic control in patients at risk for diabetes. In pursuit of this goal, one prior small-scale pilot study in overweight and obese parent-child dyads suggests that remotely delivered EFT, combined with nutritional education, holds promise in this regard (Sze et al., 2015). Future and ongoing work seeks to examine the replicability and scalability of these findings in the context of obesity and the capacity of EFT for preventing the transition to type 2 diabetes.

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References

Adler NE, Epel ES, Castellazzo G, & Ickovics JR (2000). Relationship of subjective and objective social status with psychological and physiological functioning: Preliminary data in healthy, White women. Health Psychology: Official Journal of the Division of Health Psychology, American Psychological Association, 19(6), 586.

American Diabetes Association. (2013). Economic costs of diabetes in the US in 2012. Am Diabetes Assoc. http://care.diabetesjournals.org/content/36/4/1033.short

Amlung M, Petker T, Jackson J, Balodis I, & MacKillop J (2016). Steep discounting of delayed monetary and food rewards in obesity: a meta-analysis. Psychological Medicine, 46(11), 2423–2434. [PubMed: 27299672]

Atance CM, & O'Neill DK (2001). Episodic future thinking. Trends in Cognitive Sciences, 5(12), 533–539. [PubMed: 11728911]

Bickel WK, Wilson AG, Chen C, Koffarnus MN, & Franck CT (2016). Stuck in Time: Negative Income Shock Constricts the Temporal Window of Valuation Spanning the Future and the Past. PloS One, 11(9), e0163051. [PubMed: 27631760]

Borges AM, Kuang J, Milhorn H, & Yi R (2016). An alternative approach to calculating Area-Under-the-Curve (AUC) in delay discounting research. Journal of the Experimental Analysis of Behavior, 106(2), 145–155. [PubMed: 27566660]

Centers for Disease Control and Prevention. (2017). National Diabetes Statistics Report, 2017: estimates of diabetes and its burden in the United States. 2017.

Cohen J (1992). Statistical power analysis. Current Directions in Psychological Science, 1(3), 98–101.

Crager MR (1987). Analysis of covariance in parallel-group clinical trials with pretreatment baselines. Biometrics, 43(4), 895–901. [PubMed: 3427174]

Daniel TO, Said M, Stanton CM, & Epstein LH (2015a). Episodic future thinking reduces delay discounting and energy intake in children. Eating Behaviors, 18, 20–24. [PubMed: 25863227]

Daniel TO, Said M, Stanton CM, & Epstein LH (2015b). Episodic future thinking reduces delay discounting and energy intake in children. Eating Behaviors, 18, 20–24. [PubMed: 25863227]

Daniel TO, Stanton CM, & Epstein LH (2013a). The future is now: reducing impulsivity and energy intake using episodic future thinking. Psychological Science, 24(11), 2339–2342. [PubMed: 24022653]

Daniel TO, Stanton CM, & Epstein LH (2013b). The future is now: comparing the effect of episodic future thinking on impulsivity in lean and obese individuals. Appetite, 71, 120–125. [PubMed: 23917063]

Du W, Green L, & Myerson J (2002). Cross-Cultural Comparisons of Discounting Delayed and Probabilistic Rewards. The Psychological Record, 52(4), 479–492.

Epstein LH, Jankowiak N, Fletcher KD, Carr KA, Nederkoorn C, Raynor HA, & Finkelstein E (2014). Women who are motivated to eat and discount the future are more obese. Obesity , 22(6), 1394–1399. [PubMed: 24311480]

Epstein LH, Paluch RA, Stein JS, Mellis AM, Quattrin T, Mastrandrea LD, ... & Bickel WK (2019). Role of delay discounting in predicting change in HBA1c for individuals with prediabetes. Journal of behavioral medicine, 42(5), 851–859. [PubMed: 30903441]

Epstei LH., Paluc RA., Stei JS., Quattri T., Mastrandre LD., Bre KA., ... & Bickel WK. (2020). Delay discounting, glycemic regulation and health behaviors in adults with prediabetes. Behavioral Medicine. Advance Online Publication.

Figlewicz DP (2003). Insulin, food intake, and reward. Seminars in Clinical Neuropsychiatry 8(2), 82–93. [PubMed: 12728408]

Figlewicz DP, Bennett JL, Naleid AM, Davis C, & Grimm JW (2006). Intraventricular insulin and leptin decrease sucrose self-administration in rats. Physiology & Behavior, 89(4), 611–616. [PubMed: 17045623]

Figlewicz DP, & Benoit SC (2009). Insulin, leptin, and food reward: update 2008. American Journal of Physiology-Regulatory, Integrative and Comparative Physiology, 296(1), 9–19.

Frison L, & Pocock SJ (1992). Repeated measures in clinical trials: analysis using mean summary statistics and its implications for design. Statistics in Medicine, 11(13), 1685–1704. [PubMed: 1485053]

Garza KB, Ding M, Owensby JK, & Zizza CA (2016). Impulsivity and Fast-Food Consumption: A Cross-Sectional Study among Working Adults. Journal of the Academy of Nutrition and Dietetics, 116(1), 61–68. [PubMed: 26095434]

Haushofer J, Schunk D, & Fehr E (2013). Negative income shocks increase discount rates. Working Paper http://www.princeton.edu/joha/publications/Haushofer_et_al_Negative_Income_Shocks_2013.pdf

Heron M (2018). Deaths: Leading Causes for 2016. National Vital Statistics Reports: From the Centers for Disease Control and Prevention, National Center for Health Statistics, National Vital Statistics System, 67(6), 1–77.

Johnson MW, & Bickel WK (2008). An algorithm for identifying nonsystematic delay-discounting data. Experimental and Clinical Psychopharmacology, 16(3), 264–274. [PubMed: 18540786]

Koffarnus MN, Franck CT, Stein JS, & Bickel WK (2015). A modified exponential behavioral economic demand model to better describe consumption data. Experimental and Clinical Psychopharmacology, 23(6), 504–512. [PubMed: 26280591]

Lin H, & Epstein LH (2014). Living in the moment: effects of time perspective and emotional valence of episodic thinking on delay discounting. Behavioral Neuroscience, 128(1), 12–19. [PubMed: 24512061]

Mazur JE (1987). An adjusting procedure for studying delayed reinforcement. Commons ML. ; Mazur JE. ; Nevin JA, 55–73.

Mellis AM, Athamneh LN, Stein JS, Sze YY, Epstein LH, & Bickel WK (2018). Less is more: Negative income shock increases immediate preference in cross commodity discounting and food demand. Appetite, 129, 155–161. [PubMed: 29959952]

Mellis AM, Snider SE, & Bickel WK (2018). Narrative theory: II. Self-generated and experimenter-provided negative income shock narratives increase delay discounting. Experimental and Clinical Psychopharmacology, 26(2), 113–118. [PubMed: 29337585]

Mellis AM, Snider SE, Deshpande HU, LaConte SM, & Bickel WK (2019). Practicing prospection promotes patience: Repeated episodic future thinking cumulatively reduces delay discounting. Drug and Alcohol Dependence, 204, 107507. [PubMed: 31520923]

Myerson J, Green L, & Warusawitharana M (2001). Area under the curve as a measure of discounting. Journal of the Experimental Analysis of Behavior, 76(2), 235–243. [PubMed: 11599641]

O'Donnell S, Oluyomi Daniel T, & Epstein LH (2017). Does goal relevant episodic future thinking amplify the effect on delay discounting? Consciousness and Cognition, 51, 10–16. [PubMed: 28282631]

O'Neill J, Daniel TO, & Epstein LH (2016). Episodic future thinking reduces eating in a food court. Eating Behaviors, 20, 9–13. [PubMed: 26562686]

Perreault L, Pan Q, Mather KJ, Watson KE, Hamman RF, Kahn SE, & Diabetes Prevention Program Research Group. (2012). Effect of regression from prediabetes to normal glucose regulation on long-term reduction in diabetes risk: results from the Diabetes Prevention Program Outcomes Study. The Lancet, 379(9833), 2243–2251.

Peters J, & Büchel C (2010). Episodic future thinking reduces reward delay discounting through an enhancement of prefrontal-mediotemporal interactions. Neuron, 66(1), 138–148. [PubMed: 20399735]

Riddle M, & Science of Behavior Change Working Group. (2015). News from the NIH: using an experimental medicine approach to facilitate translational research. Translational Behavioral Medicine, 5(4), 486–488. [PubMed: 26622921]

Senn SJ (1989). Covariate imbalance and random allocation in clinical trials. Statistics in Medicine, 8(4), 467–475. [PubMed: 2727470]

Snider SE, DeHart WB, Epstein LH, & Bickel WK (2019). Does delay discounting predict maladaptive health and financial behaviors in smokers? Health Psychology: Official Journal of the Division of Health Psychology, American Psychological Association, 38(1), 21–28.

Snider SE, Deshpande HU, & Lisinski JM (2017). Working memory training improves alcohol users' episodic future thinking: a rate dependent analysis. Biological Psychiatry. https://www.sciencedirect.com/science/article/pii/S245190221730201X

Snider SE, LaConte SM, Bickel WK. (2016). Episodic Future Thinking: Expansion of the Temporal Window in Alcohol Dependents. Alcoholism, Clinical and Experimental Research.

Snider SE, LaConte SM, & Bickel WK (2016). Episodic Future Thinking: Expansion of the Temporal Window in Individuals with Alcohol Dependence. Alcoholism, Clinical and Experimental Research, 40(7), 1558–1566.

Stein JS, Koffarnus MN, Snider SE, Quisenberry AJ, & Bickel WK (2015). Identification and management of nonsystematic purchase task data: Toward best practice. Experimental and Clinical Psychopharmacology, 23(5), 377. [PubMed: 26147181]

Stein JS, Sze YY, Athamneh L, Koffarnus MN, Epstein LH, & Bickel WK (2017). Think fast: rapid assessment of the effects of episodic future thinking on delay discounting in overweight/obese participants. Journal of Behavioral Medicine, 1–7.

Stein JS, Wilson AG, Koffarnus MN, Daniel TO, Epstein LH, & Bickel WK (2016). Unstuck in time: episodic future thinking reduces delay discounting and cigarette smoking. Psychopharmacology. 10.1007/s00213-016-4410-y

Sze YY, Daniel TO, Kilanowski CK, Collins RL, & Epstein LH (2015). Web-Based and Mobile Delivery of an Episodic Future Thinking Intervention for Overweight and Obese Families: A Feasibility Study. JMIR mHealth and uHealth, 3(4), e97. [PubMed: 26678959]

Sze YY, Stein JS, Bickel WK, Paluch RA, & Epstein LH (2017). Bleak Present, Bright Future: Online Episodic Future Thinking, Scarcity, Delay Discounting, and Food Demand. Clinical Psychological Science, 5(4), 683–697. [PubMed: 28966885]

Tabák AG, Herder C, Rathmann W, Brunner EJ, & Kivimäki M (2012). Prediabetes: a high-risk state for diabetes development. The Lancet, 379(9833), 2279–2290.

Tiedemann LJ, Schmid SM, Hettel J, Giesen K, Francke P, Büchel C, & Brassen S (2017). Central insulin modulates food valuation via mesolimbic pathways. Nature Communications, 8(1), 1–10.

Weller RE, Cook EW, Avsar KB, & Cox JE (2008). Obese women show greater delay discounting than healthy-weight women. Appetite, 51(3), 563–569. [PubMed: 18513828]

Yoon JH, De La Garza R 2nd, Newton TF, Suchting R, Weaver MT, Brown GS, Omar Y, & Haliwa I (2017). A comparison of Mazur's k and area under the curve for describing steep discounters. The Psychological Record, 67(3), 355–363. [PubMed: 28970640]

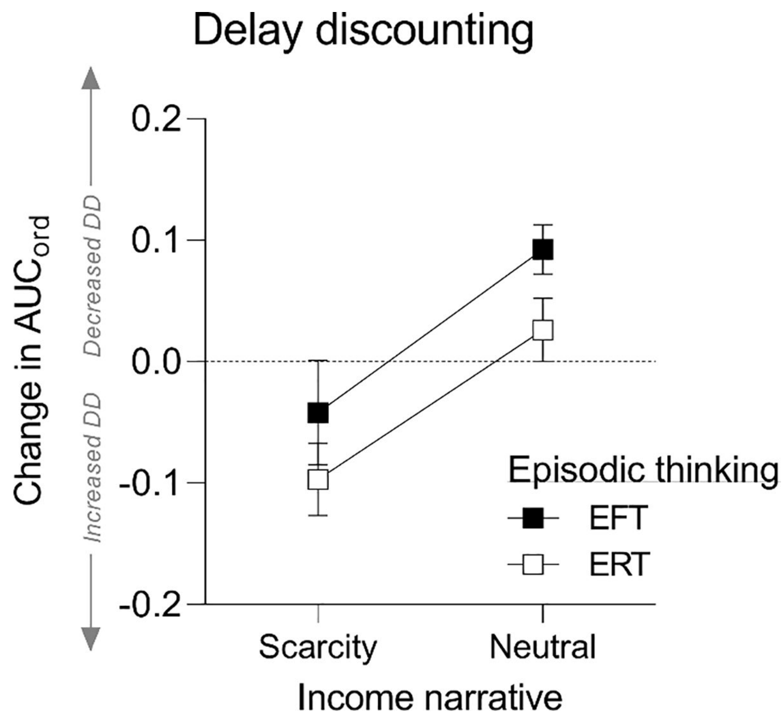

Figure 1.

Change in delay discounting (AUC$_{ord}$) between Session 1 (baseline) and Session 2 (interventions) in episodic thinking and income narrative conditions. Error bars represent standard error of the mean. Results indicated significant main effects of episodic thinking condition ($p < .05$) and income narrative ($p < .01$), with no significant interactions between factors.

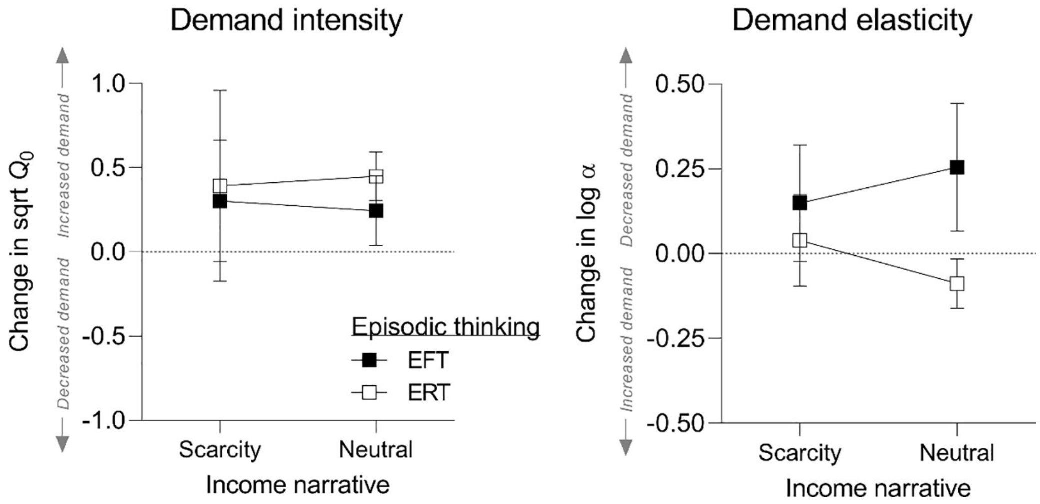

Figure 2.

Change in demand intensity (square root Q0) and elasticity (log α) between Session 1 (baseline) and Session 2 (interventions) in episodic thinking and income narrative conditions. Error bars represent standard error of the mean. Results indicated no significant main effects or interactions between conditions for either measure.

Table 1.

Participant characteristics and sample sizes.

Episodic thinking group	EFT		ERT	
Income narrative group	**Scarcity**	**Neutral**	**Scarcity**	**Neutral**
n	21	20	18	19
Age (±SD)	47.57 (12.72)	50.55 (14.39)	50.61 (10.41)	52.89 (11.38)
Mean BMI (±SD)	37.50 (8.83)	34.45 (6.75)	38.97 (7.68)	40.44 (10.90)
Mean HbA1c (±SD)	5.67 (0.21)	5.73 (0.25)	5.76 (0.30)	5.72 (0.22)
HbA1c ranges				
% 5.4–5.6 (*n*)	52.38 (11)	50.00 (10)	55.55 (10)	47.37 (9)
% 5.7–6.4 (*n*)	47.62 (10)	50.00 (10)	44.44 (8)	52.63 (10)
Mean \$100 AUC_{ord} (±SD)	0.54 (0.16)	0.49 (0.17)	0.52 (0.18)	0.51 (0.20)
Mean \$1000 AUC_{ord} (±SD)	0.61 (0.19)	0.57 (0.21)	0.60 (0.23)	0.59 (0.20)
Education				
% HS/GED or lower (*n*)	14.29 (3)	20.00 (4)	11.11 (2)	10.53 (2)
% Some college (*n*)	47.62 (10)	40.00 (8)	55.55 (10)	42.11 (8)
% College degree or greater (*n*)	38.09 (8)	40.00 (8)	33.33 (6)	47.34 (9)
Gender				
% Female (*n*)	80.95 (17)	75.00 (15)	72.22 (13)	84.21 (16)
% Male (*n*)	19.05 (4)	25.00 (5)	27.78 (5)	15.79 (3)
Household income				
% < \$50,000 (*n*)	57.14 (12)	45.00 (9)	61.11 (11)	42.11 (8)
% ≥ \$50,000 (*n*)	42.86 (9)	50.00 (10)	33.33 (6)	57.89 (11)
% Refused/missing (*n*)	0.00 (0)	5.00 (1)	5.56 (1)	0.00 (0)
Race/ethnicity				
% Minority (*n*)	47.62 (10)	45.00 (9)	72.22 (13)	47.39 (9)
% Non-minority (*n*)	52.38 (11)	55.00 (11)	22.22 (4)	52.63 (10)
% Refused/missing (*n*)	0.00 (0)	0.00 (0)	5.56 (1)	0.00 (0)
Site				
% VT (*n*)	42.85 (9)	35.00 (7)	38.89 (7)	42.11 (8)
% UB (*n*)	57.14 (12)	65.00 (13)	61.11 (11)	57.89 (11)

BMI body mass index; *HbA1c* Hemoglobin A1c (%); *HS/GED* high school/general equivalency diploma