The Effect of Episodic Future Thinking on a Novel Measure of Behavioral Economic Demand for Exercise

Jeremiah Michael Brown

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Jeffrey S. Stein, Chair
George C. Davis
Alexandra G. DiFeliceantonio
Michelle S. Rockwell

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ABSTRACT

Physical inactivity is a major contributor to increased disease prevalence and reduced quality of life. Measuring behavioral economic demand for exercise may enable more effective physical activity intervention development. In study one, we developed the leisure-time-as-price exercise purchase task (LT-EPT), wherein participants (*n* = 175) indicate hypothetical likelihood to trade leisure time for access to exercise time. We observed weak to moderate correlations between demand indices ($Q_{1\%}$, α, BP_1, and P_{max}) generated from the LT-EPT and self-reported leisure and exercise time, demonstrating initial validation of the LT-EPT. In study two, we examine the effect of episodic future thinking (EFT; vivid, personalized prospection of future events) in adults not meeting physical activity guidelines (*n* = 127) on demand for exercise and delay discounting (sensitivity to delayed rewards). We observed reduced delay discounting in participants randomized to engage in EFT, but no difference between EFT and health information thinking (HIT) controls. In study three, we further examined the effect of EFT on demand for exercise in adults with type 2 diabetes and obesity participating in a 24-week randomized controlled trial (*n* = 71). All participants engaged in a multicomponent behavioral intervention focused on weight loss and glycemic control; additionally, participants were randomized to engage in EFT or HIT thrice daily beginning in week 3. We measured demand for exercise and delay discounting (among other outcomes) at weeks 0, 8, and 24, observing no differences between EFT or HIT groups in demand indices ($Q_{1\%}$, α) or delay discounting at any time point. In conclusion, early evidence suggests that the LT-EPT may be a valid method to measure behavioral economic demand for exercise; however, EFT may not be an effective intervention to increase demand for exercise.

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GENERAL AUDIENCE ABSTRACT

Physical inactivity poses a significant threat to our well-being, contributing to increased disease rates and a diminished quality of life. This dissertation details a novel method to measure how people value exercise and the effect of a behavioral intervention to increase exercise valuation. In the first study, we introduce the leisure-time-as-price exercise purchase task (LT-EPT), a tool designed to gauge individuals' willingness to trade leisure time for exercise time (i.e., exercise demand). Initial results show promising correlations between LT-EPT metrics and self-reported leisure and exercise time, providing a foundation for its potential as a valuable measurement tool. The second study examines the impact of episodic future thinking (EFT), a technique involving vivid and personalized visualization of future events, on exercise demand. While participants engaging in EFT showed increased preference for larger, delayed rewards over smaller, sooner rewards (i.e., reduced delay discounting), no significant difference was found between EFT and the health information thinking (HIT) control in terms of exercise demand. The third study expands our investigation to adults with type 2 diabetes and obesity undergoing a 24-week intervention. All participants engaged in a comprehensive behavioral program, while half were randomized to engage in EFT or HIT three times per day. No discernible differences were observed in exercise demand or delay discounting at any measurement point. In summary, our findings suggest that the LT-EPT may be a valid measure of exercise demand. However, the effectiveness of EFT in increasing demand for exercise remains inconclusive. These insights contribute to the ongoing efforts to develop more targeted and impactful interventions for promoting physical activity and improving overall health.

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ATTRIBUTIONS

Manuscript one was co-authored with Emi Miyazaki and Jeffrey S. Stein. Manuscripts two and three were co-authored with Jeffrey S. Stein.

INTRODUCTION

Physical Inactivity, Obesity, and Type 2 Diabetes

About 80% of American adults and adolescents are not meeting physical activity guidelines, despite the considerable immediate and delayed health benefits associated with regular physical activity (Piercy et al., 2018). It is estimated that 8.3% of premature deaths can be attributed to physical inactivity, and that inactive adults incur 26.6% greater healthcare expenditure than active adults (Carlson, 2018; Carlson et al., 2015). Additionally, the age-adjusted prevalence of American adults with obesity was estimated to be 42.4% in 2017-2018 (Hales, 2020), while 11.3% of the US population are estimated to have type 2 diabetes (CDC, 2022). On average, individuals with type 2 diabetes engage in less physical activity than those without the disease (Zhao et al., 2008). A meta-analysis of prospective cohort studies estimates that meeting the U.S. Department of Health and Human Services' physical activity guidelines of 150 minutes of moderate-physical activity each week (Piercy et al., 2018) may decrease the risk of developing type 2 diabetes by 26% relative to physical inactivity (Smith et al., 2016)**.** Increased engagement in physical activity can have major positive metabolic and cardiovascular health outcomes (including weight loss and glycemic control) in these populations (Laskowski, 2012), highlighting the need for translational research to better understand the value of exercise and inform health behavior change strategies.

Measuring the Reinforcing Value of Exercise

A reinforcer is a stimulus or behavior which, when delivered or engaged in, results in an increase in behaviors that preceded the stimulus (Skinner, 1938). Reinforcing value (or efficacy) can be defined as the ability of a reinforcer to sustain behavior (Johnson & Bickel, 2006). Exercise (planned physical activity done to improve or maintain fitness; Caspersen et al., 1985) can function as a reinforcing stimulus, and the reinforcing value of exercise functions as one of many components influencing the choice to engage in exercise or sedentary behaviors (Flack et al., 2019). Improving our understanding of measuring the reinforcing value of exercise could lead to valuable insights regarding the neurological or behavioral characteristics of individuals with varying valuation for exercise, and help to identify interventions that may increase the valuation of exercise and lead to increased rates of physical activity (Carr & Epstein, 2020). To date, two approaches have been used to measure the reinforcing value of exercise: relative reinforcing value and operant behavioral economic demand. Relative reinforcing value approaches measure how much work an organism will perform in order to gain access to a reinforcer relative to another reinforcer. Operant behavioral economic demand approaches may utilize purchase tasks, in which an organism is able to defend consumption of a commodity across escalating prices. While the strengths and weaknesses of each approach will be discussed in more detail in Chapter 2, both approaches have been used to quantify the construct of reinforcing value.

I have previously published work utilizing operant behavioral economic demand for gym membership as a proxy to measure the reinforcing value of exercise (Brown et al., 2021). Demand—the extent to which an organism will defend consumption of a commodity across escalating prices—can be measured using hypothetical purchase tasks, in which participants report their hypothetical consumption of a good (Roma et al., 2017). In the gym membership purchase task (GMPT), participants indicate their likelihood of purchasing one month of membership at their ideal gym across a range of prices. However, the GMPT is limited in two major areas. First, demand for gym membership may not map on to demand for volitional exercise for a large segment of the population. Many individuals engage in various forms of exercise outside of the gym or similar fitness-centric environments (e.g., hiking, skiing, dancing, gardening), or may find these environments aversive. Second, for many inactive individuals, the most relevant cost to engaging in regular exercise is not paid via monetary costs (i.e., via gym membership) but instead via time and the opportunity cost to engage in other, potentially more reinforcing behaviors (i.e., leisure time). While certain physical activities may be less convenient in certain built environments (e.g., walking in rural areas), most individuals could find ways to increase their physical activity without purchasing a gym membership or incurring monetary costs; however, any time allocated to exercise comes at the expense of time that cannot be allocated to other behaviors, including leisure time, work, sleep, activities of daily living (e.g., childcare, food preparation, personal hygiene), or social activities.

To address these limitations of the GMPT and previous operant behavioral economic approaches to measure the reinforcing value of exercise, the first study of this dissertation will describe the development and validation of a novel hypothetical purchase task in which the cost to engage in exercise is not monetary, but instead incurred through a reduction of leisure time (Study one). The *leisure-time-as-cost exercise purchase task* will ask participants to indicate their self-reported likelihood of sacrificing a given amount of leisure time (relative to self-reported total available leisure time) in order to allocate that time to engage in exercise. The units of leisure time to be sacrificed will be expressed as a percentage of the total leisure time a participant has during a typical week (including weekends). Self-reported likelihood of allocating leisure time to exercise will be reported on a scale of 0 to 100 across escalating percentages of weekly leisure time, allowing for the plotting of a demand curve to model hypothetical likelihood to sacrifice leisure time for exercise time across escalating amounts of leisure time. Studies two and three will examine the effect of episodic future thinking (EFT) on demand for exercise evaluated using the novel leisure-time-as-cost exercise purchase task and other measures (e.g., delay discounting, self-reported physical activity) in clinically relevant samples (e.g., individuals not meeting physical activity guidelines, individuals with obesity and type 2 diabetes.

Delay Discounting

In the natural environment, humans are faced with choices which may attenuate the likelihood of negative or positive future health outcomes. Such choices reflect aspects of decision making that contrast immediate rewards of smaller value with delayed rewards of greater value. Delay discounting, a process by which rewards decrease in value as the delay to their receipt increases, can be considered a measure of delayed consequence sensitivity (Madden & Johnson, 2010; Strickland & Johnson, 2021). For example, the choice to continue a sedentary activity (e.g., watching television) instead of engaging in physical activity can be conceptualized as choosing an immediately reinforcing behavior (TV watching) at the expense of experiencing delayed positive health outcomes as a consequence of physical activity. In this way, the likelihood of engaging in physical activity may be partially influenced by sensitivity to delayed consequences.

Delay discounting is cross-sectionally and longitudinally associated with a range of maladaptive health behaviors and lifestyle-related diseases (Bickel et al., 2012). For example, higher rates of delay discounting are associated with greater energy consumption, more sedentary activity, and higher body mass index (BMI; Amlung et al., 2016), as well as cigarette smoking (Audrain-McGovern et al., 2009; Bickel et al., 1999) and other substance use (Stein & Madden, 2013). Additionally, steeper rates of delay discounting are correlated with higher rates of behavioral economic demand for alcohol (MacKillop et al., 2010). Finally, individuals with steeper rates of delay discounting and higher relative reinforcing value of food tend to consume more calories than individuals with less steep rates of delay discounting and similar relative reinforcing value of food (Rollins et al., 2010). These findings suggest that steep rates of delay discounting and high rates of reinforcing value for deleterious commodities are separate processes that increase the risk of unhealthy patterns of behaviors (i.e., reinforcer pathology; (Bickel, 2017; Bickel et al., 2012; DeHart et al., 2020).

To the best of the author's knowledge, only one study has examined correlations between delay discounting (of both money and exercise) and operant behavioral economic demand for exercise (May, 2020). May (2020) observed a small but significant correlation between delay discounting of monetary rewards and essential value of exercise, indicating that individuals with less steep rates of delay discounting demonstrated greater reinforcing value of exercise. In some ways, these findings can be conceptualized as the absence of reinforcer pathology: a phenomenon when lower rates of delayed reward sensitivity are associated with increased valuation of temporally delayed rewards (e.g., positive health outcomes following physical activity). However, operant behavioral economic demand for exercise as measured by May (2020) utilized money as the cost incurred to gain access to exercise. Similar to the gym membership purchase task, using money as the cost incurred to gain access to exercise does not reflect the real-world sacrifice of time that must be made to engage in exercise. It is unclear whether high levels of operant behavioral economic demand for exercise using the leisure-time-as-cost purchase task will be associated with less steep rates of delay discounting or higher rates of physical activity. Furthermore, it is unclear whether such a relationship exists in clinically relevant populations (e.g., individuals not meeting physical activity guidelines, individuals with type 2 diabetes mellitus), or how behavioral interventions that reduce delay discounting and demand for health-relevant commodities will impact delay discounting and demand for exercise in these populations.

Episodic Future Thinking

Episodic future thinking is the act of imagining personal future events and experiences in great detail (Atance & O'Neill, 2001). Engagement in EFT tends to reduce delay discounting across a variety of populations (Daniel et al., 2013, 2015; Rung & Epstein, 2020; Rung & Madden; Stein et al., 2016, 2018). While the mechanisms underlying the effect of EFT on delay discounting are unclear, it has been speculated that effects are due to an increased ability to consider the utility of temporally delayed rewards in the present moment (Lin & Epstein, 2014). EFT also influences behavioral outcomes relevant to health. Specifically, brief engagement in EFT in the laboratory has been shown to reduce caloric consumption of highly palatable foods during an ad-libitum eating task in adults and children with overweight/obesity (Daniel et al., 2013, 2015) and in young adults, where the effect of EFT on decreased consumption of chocolate confections was moderated by higher BMI values (Chang et al., 2020), and the purchase of high calorie and low nutrient foods in an online grocery shopping task (Hollis-Hansen et al., 2019). Brief engagement in EFT has also been shown to decrease self-administration of cigarettes and hypothetical cigarette demand in current smokers (Chiou & Wu, 2017; Stein et al., 2016, 2018), and hypothetical alcohol demand in individuals with alcohol use disorder (Bulley & Gullo, 2017; Patel & Amlung, 2020; Snider et al., 2016).

In naturalistic settings, repeated delivery of EFT has been used to reduce total calorie consumption and calories from fat in women with overweight/obesity in a food court (O'Neill et al., 2016) and has been demonstrated to reduce calories, grams of fat, and milligrams of sodium purchased by mothers with overweight/obesity who engage in grocery shopping for their household (Hollis-Hansen et al., 2020). Additionally, regular engagement in EFT may improve health behavior not related to dietary intake, including medication adherence in adults with type 2 diabetes or prediabetes (Epstein, Jimenez-Knight, et al., 2022) and alcohol consumption in adults with a desire to reduce their drinking (Athamneh et al., 2021).

While the effects of EFT on delay discounting and related health-behaviors appear promising, it is unclear how EFT affects physical activity or operant behavioral economic demand for exercise. Presently, only one clinical trial has examined the effects of repeated engagement in EFT on exercise, finding no effect of EFT (Epstein, Paluch, et al., 2022). Unsuccessful translation of EFT to increase physical activity in clinical settings highlights the need of basic research to elucidate the conditions (if any) in which EFT may promote increased physical activity or physical activity valuation. Epstein, Paluch, et al. (2022) used a complex, multi-component clinical trial; a simpler design delivering acute EFT (without additional intervention components encouraging physical activity) is needed to examine the effects of EFT on exercise valuation in isolation (Study 2). Additionally, further examination of the potential effects of repeated EFT engagement on actual physical activity behaviors and valuation in clinically relevant samples (e.g., individuals with T2DM) are warranted (Study 3).

Proposed Studies

To fill these gaps, additional work is needed to: 1) develop a widely disseminable and ecologically valid assessment of the reinforcing value of exercise, 2) examine the effects of EFT on the reinforcing value of physical activity in physically inactive adults, and 3) examine the effect of EFT on physical activity and demand for exercise in adults with obesity and type 2 diabetes. To this end, I am proposing a series of three related studies.

Study 1

Research question: Can the reinforcing value of exercise be effectively measured using a hypothetical purchase task in which the price or cost to engage in exercise is incurred through a reduction in leisure time? If so, does this task demonstrate stronger construct validity than the likelihood GMPT? *Hypothesis:* The leisure-time-as-cost exercise purchase task (LT-EPT) will effectively measure value for exercise and demonstrate stronger construct validity than the GMPT, as measured by systematic data (i.e., reduced likelihood of allocating leisure time to exercise time as the amount of leisure time that must be sacrificed increases), and correlations between demand indices and self-reported exercise behaviors. This study will recruit American adults using Amazon Mechanical Turk, an online crowdsourcing platform commonly used in behavioral research (Paolacci et al., 2010). Participants will complete a Qualtrics survey in which they will be randomly assigned to the LT-EPT exercise purchase task or the GMPT; additionally, participants will answer demographic questions and provide information about their physical activity habits. Data collection will occur in the fall of 2022, with analysis finishing by the spring of 2023.

Study 2

Research question: What is the effect of acute (i.e., single exposure) EFT on behavioral economic demand for exercise and delay discounting in physically inactive adults compared to the Healthy Information Thinking (HIT), a health-relevant informational control condition? *Hypothesis:* EFT will increase demand for exercise and reduce delay discounting relative to the HIT condition. Participants will complete a single session, online survey in which they answer demographic questions, are randomized to EFT or HIT conditions, generate EFT or HIT cues, then complete a delay discounting and the leisure-time-as-cost exercise purchase task while instructed to vividly imagine their cues. Data collection will occur in the spring of 2023, with analysis finishing by the fall of 2023.

Study 3

Research question: What is the effect of repeated delivery of EFT compared to HIT on delay discounting, demand for exercise, and self-reported physical activity following 8 weeks of participation in a behavioral intervention targeting weight loss and blood sugar control in adults with type 2 diabetes and obesity? *Hypothesis:* Participants randomized to the EFT condition will have reduced delay discounting and increased demand for exercise compared to HIT participants. Additionally, participants engaging in EFT will have greater self-reported physical activity than HIT participants. The data required to test this hypothesis will be collected in the context of a fully remote 24-week clinical trial targeting reduced BMI and HbA1c as primary outcomes. All participants will receive a standardized behavioral intervention including self-monitoring tools, behavioral coaching, and educational modules; additionally, participants will be randomized to EFT or HIT conditions and instructed to engage with EFT or HIT cues 3 times per day, beginning in week 3. Data collection will begin in the summer of 2022 and continue until the spring of 2024, with analysis finishing by the spring of 2024.

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REVIEW OF LITERATURE

Relative Reinforcing Value

Relative reinforcing value (RRV) is defined as the extent to which an organism will work to gain access to one reinforcer relative to another reinforcer (Pierce & Epling, 1983). In other words, RRV can be considered a measure of the reinforcing value of one reward relative to another. RRV may be determined by arranging a concurrent choice procedure, in which participants can choose to work in order to gain access to two reinforcers (e.g., five minutes of sedentary activity vs. five minutes of physical activity). Participants are able to engage in an operant response (e.g., mouse button clicks) to meet the active schedule of reinforcement for a given reinforcer (e.g., 2 clicks); afterwards, the schedule escalates, increasing the number of responses required to gain access to the reinforcer (e.g., 4 clicks). In this arrangement, participants must choose the option to which they allocate behavior and earn the associated reward. The largest schedule requirement met on a given option is termed breakpoint and is considered a measure of reinforcing value (Hodos & Kalman, 1963). As breakpoint is assessed for two reinforcers in the context of a concurrent choice procedure, the measure of reinforcing value is *relative* between the reinforcers. Experiments using this methodology have demonstrated that individual RRVs of different forms of physical activity (e.g., aerobic, resistance training) predict engagement in the corresponding modes of physical activity in adults (Flack et al., 2017) and children (Epstein et al., 1999). Relatedly, in sedentary individuals with overweight or obesity, engaging in 12 weeks of aerobic exercise increased the RRV of aerobic physical activity (Flack et al., 2019).

As a measure of exercise valuation, RRV has both limitations and strengths. The process of establishing a breakpoint in this paradigm (i.e., the price at which consumption of the commodity ceases) can be time consuming and resource intensive, as researchers must also present access to the commodity (e.g., five minutes of exercise or sedentary activity) as many times as the schedule of reinforcement was met. This experimental arrangement makes it difficult to assess the RRV of exercise longitudinally in large samples, and precludes remote assessments. Additionally, RRV is a measure of the value of a reinforcer relative to another specific reinforcer. That is, the reinforcing value of exercise described in the above studies was measured relative to the reinforcing value of sedentary activities or contrasting forms of physical activity (e.g., aerobic exercise vs. resistance training); RRV does not allow for an assessment of reinforcing value independent of the other reinforcer in the arrangement. Additionally, choices in real world settings are made between a large number of concurrently available reinforcers; RRV assessments typically only account for two concurrently available reinforcers, as interpreting the value of one reinforcer compared to two or more would be difficult. While RRV is a conceptually sound method to quantify the reinforcing value of a stimulus compared to another, the ecological validity of this approach is limited. Finally, RRV provides information about the reinforcing value of a commodity only at breakpoint; it does not provide information about value at schedule requirements preceding breakpoint (beyond those requirements being met for a given quantity of the reinforcer).

Despite these limitations, RRV is still a valuable measure with unique strengths for certain experimental designs. For example, the operant response in RRV arrangements is typically a behavior that can be repeated easily without physical fatigue becoming a limiting factor in responding (e.g., mouse button clicks, plunger pulls). This effectively controls for each participants' "income", making the observed breakpoint a reasonable estimation of relative value, despite evidence that differences in income can lead to different allocations of responses for different reinforcers (Hursh & Silberberg, 2008). However, when making decisions about behavioral allocation in real world settings, "income" (which may be conceptualized as both available time and financial resources) varies between individuals. Failing to account for differences in income within the task may limit generalizability to real-world behaviors or reinforcers with monetary consequences.

Behavioral Economic Demand

Behavioral economic demand measures the degree to which an individual defends consumption of a commodity as the price of said commodity increases (Hursh & Silberberg, 2008); thus, demand can be said to represent the value an individual places on a commodity in a given environment. Similar to RRV, demand is assessed using an experimental arrangement in which subjects must meet a specific schedule of reinforcement to obtain the commodity across escalating unit prices (i.e., response requirement for one unit of the commodity; (Hursh, 1980). One such arrangement–the purchase task–has been developed to enable assessments of demand across a broad range of commodities, including drugs of abuse, obesogenic foods, and gym membership (Brown et al., 2021; Epstein et al., 2018; Jacobs & Bickel, 1999). Purchase tasks may utilize real or hypothetical response requirements or rewards, with evidence indicating correspondence between both hypothetical and actual rewards (Amlung et al., 2012; Amlung & MacKillop, 2015). Using the purchase task framework, subjects may report the number of units of a commodity they would purchase across a range of unit prices (i.e., quantity purchase tasks; Jacobs & Bickel, 1999; MacKillop et al., 2008); similarly, subjects may report the likelihood of purchasing one unit of a commodity across a range of prices (probability of single purchase tasks; (Roma et al., 2017). Additionally, subjects are instructed to make their purchases as if certain constraints were in place; for example, that their income and savings are the same as they are now, that they must consume or use the commodity within a specific time period, that the commodity may not be shared or sold, and that their only access to the commodity is restricted to what they purchase in the task. The assumption regarding participants' income and savings allows the task to more closely approximate the real-world conditions under which economic decisions take place, potentially increasing external validity.

Data generated from hypothetical purchase tasks (i.e., hypothetical consumption across prices) can be fit to various models of demand (for review of different models, see (Koffarnus et al., 2022), allowing for the estimation of demand indices to quantify the reinforcing value of a commodity. Demand indices include: intensity of demand (Q_0), a measure of consumption at zero price; breakpoint, the last price at which purchasing occurred; *Pmax* (price maximum), the price at which demand shifts from inelastic (small or no decreases in consumption relative to increases in price) to elastic (large decrease in consumption relative to increases in price); *Omax* (output maximum), the expenditure associated with consumption at *Pmax* (i.e., the quantity demanded multiplied by unit price); and *alpha* (α), a single index quantifying the rate of change in elasticity across the entire demand curve.

Historically, demand indices have been generated using three approaches (Kaplan et al., 2021). First, using fit-to-group analyses, group level mean or median consumption at each price is fit to a model of demand and overall variability is not considered (leading to artificially small standard errors for parameter estimates and an increased probability of making a type 1 error in subsequent statistical tests). Second, using a two-stage approach, individual demand data for each participant is fit to a model of demand (stage one), followed by null-hypothesis significance testing approaches (stage two) for group comparisons. In this approach, no information about the sample is able to inform estimations of individual demand indices, and some individual consumption data may not be able to be modeled due to patterns of responding not well described by the chosen model. More recently, mixed-effects models have been utilized to estimate both group and individual level demand data, incorporating both fixed and random effects into the model and overcoming the previously described limitations. Additionally, because mixed-effects models are able to incorporate intrasubject variability in responding across different prices on a task, larger standard errors for parameter estimates are generated, decreasing the probability of committing a type 1 error in subsequent statistical tests at the group level.

Behavioral Economic Demand for Exercise

To date, there have been two attempts to measure operant behavioral economic demand for exercise. First, May (2020) developed a hypothetical exercise purchase task in which participants indicated the number of 15-minute blocks of exercise they would purchase at a given price. Second, Brown et al. (2021) developed two different versions of a hypothetical gym membership purchase task (GMPT), in which participants indicate either their likelihood of signing up for one month of membership to their ideal gym or the number of day passes to their ideal gym they would purchase to use for one month (Brown et al., 2021). In contrast to RRV assessments of exercise, hypothetical purchase tasks do not require delivering access to physical or sedentary activities following completion of the task, can be administered in-person or remotely, is sensitive to participants' income and savings, and assesses the value of exercise non-relative to a single alternative reinforcer. However, both tasks currently reported in the literature have important limitations.

While greater behavioral economic demand for gym membership has been shown to correlate with higher rates of self-reported physical activity (Brown et al., 2021), it is unknown how gym membership demand functions as a proxy for exercise demand in clinically relevant populations (e.g., adults with type 2 diabetes) or more generally. Brown et al. (2021) did not observe significant correlations between elasticity of demand indices from the probability of purchase GMPT and self-reported number of minutes spent exercising outside of a gym each week, suggesting that the task may not be sensitive to measuring value for exercise among individuals who exercise primarily outdoors. While May's (2020) exercise purchase task does not have this conceptual limitation, another limitation is created by arranging a purchase task in which money is the incurred cost for a commodity that can be "consumed" for free. Money is a highly fungible, generalized conditioned reinforcer that is widely understood by humanity, but it may not be the most relevant cost incurred when deciding to engage in increased rates of physical activity. Specifically, the most relevant cost to engaging in physical activity or exercise may be incurred on our most precious and finite resource: time. Physical activity and exercise is more often limited primarily, not by financial constraints, but by time and effort. Thus, the degree to which an individual defends consumption of exercise across escalating costs of leisure time may be a more conceptually valid measure of the reinforcing value of exercise than a task utilizing money as the cost. Additionally, the time-as-cost approach allows for a purchase task in which exercise is the commodity under evaluation, not gym membership as a proxy for exercise.

A hypothetical purchase task for exercise using leisure time as the cost would overcome the limitations described above and represent a novel contribution to the literature on behavioral economic demand while potentially furthering our understanding of exercise as a valuable and reinforcing commodity (study one). Additionally, it is unclear under what conditions demand for exercise may be increased in clinically relevant populations, or predict treatment efficacy. Studies two and three would shed light on how demand for exercise may or may not change in response to behavioral interventions in populations that would benefit from increased physical activity, including individuals not meeting physical activity guidelines or individuals with T2DM.

Summary

Relative reinforcing value using behavioral costs (e.g., button presses) is a valid method of comparison between two commodities, but this approach can be difficult to implement for some reinforcers and does not reflect real-world choice scenarios in which multiple commodities are available (e.g., a range of sedentary leisure behaviors vs. exercise). Behavioral economic demand approaches utilizing hypothetical purchase tasks overcome some of these limitations inherent to measuring the reinforcing value of exercise. Previous approaches using demand have used money as the hypothetical cost to engage in exercise; however, time may be more relevant for this specific activity.

Delay Discounting Overview

Delay discounting is a process by which the value of a stimulus decreases as a function of the delay before receiving the stimulus (Odum, 2011). Delay discounting is measured using observations of behavior, from lever presses in rats, key pecks in pigeons, to choices between hypothetical or real outcomes in humans (e.g., choosing between $100 now or $200 in one month; Madden & Johnson, 2009). Regardless of the method or species, delay discounting tasks assess the point at which two rewards of different amounts and delays are perceived as equal, termed an indifference point. The indifference point represents the present value of the delayed reward, or the extent to which the present value of the delayed reward is discounted as a result of the delay.

Indifference points can be plotted as a function of the delay associated with the larger later rewards, and the resulting curve from this plot (a discounting curve; see figure 1), is typically well defined by a hyperbolic nonlinear regression model ($V = A/(1 + kD)$; Mazur, 1987). In this equation, V (the indifference point) is equal to the amount (A) of the larger later reward divided by the sum of one plus the delay (D) multiplied by *k*, the only free parameter in the model. Solving for *k* allows for a measurement of the degree to which the organism discounts the future. Larger *k* values are derived from steeper discounting curves and indicate higher rates of delay discounting, while smaller *k* values are derived from shallower discounting curves and indicate lower rates of delay discounting. Alternatively, delay discounting can be measured without the use of a hyperbolic nonlinear regression (or other) model, by normalizing delays and indifference points and calculating the area under the discounting curve (AUC; Myerson et al., 2001). The AUC will range from 0 to 1; if the discounting curve were a flat line starting from the normalized maximum value of one (i.e., the organism only chose the larger later), the AUC would be 1.

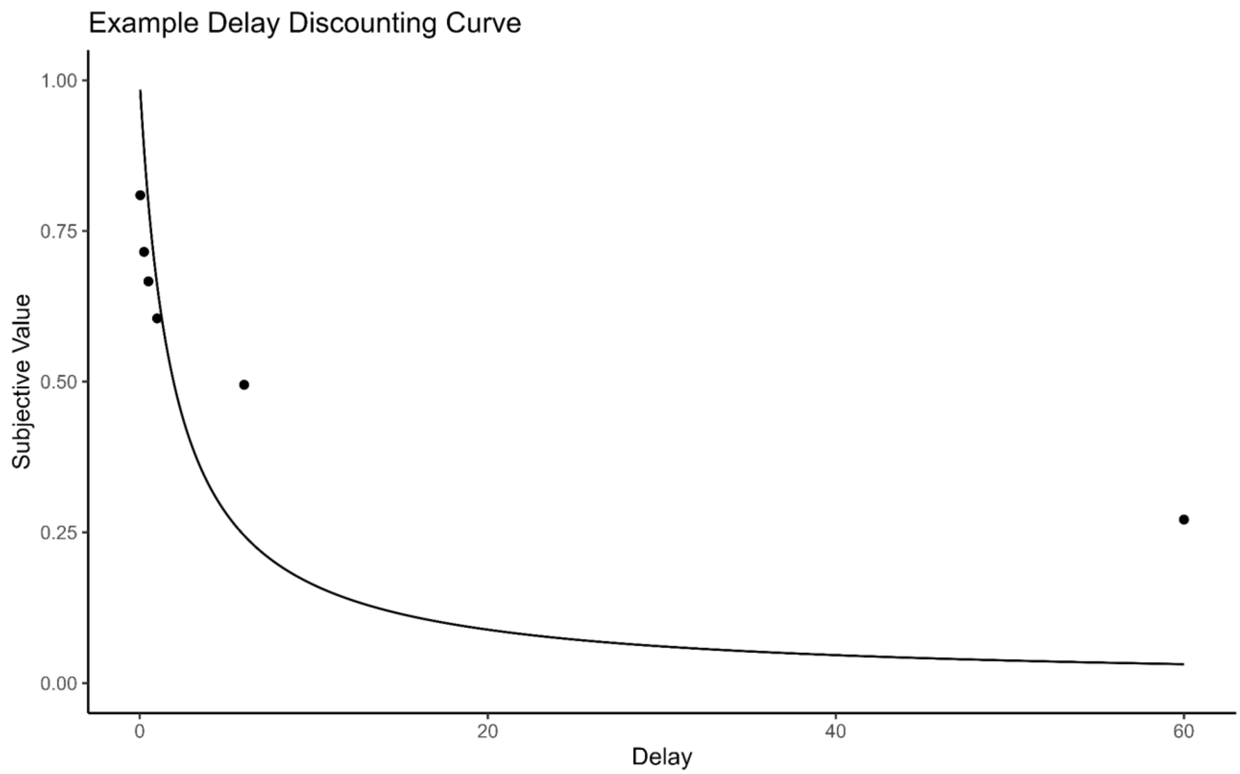

Figure 1: Example delay discounting curve, created using a subset of data collected from a $100 gain delay discounting task (DeHart et al., 2020). Points depict observed mean subjective value across delay; the line depicts predicted subjective value across delay according to Mazur's hyperbolic equation (1987).

Delay Discounting and Obesity

There is a large body of literature examining the relationship between delay discounting and obesity. Higher rates of delay discounting have been observed to correlate with higher rates of obesity, type 2 diabetes, and physical inactivity (Amlung et al., 2016; Barlow et al., 2016; Lebeau et al., 2016; Reach et al., 2011; Sofis et al., 2017; Tang et al., 2019). It has been theorized that delay discounting operates as a trans-disease process underlying a range of maladaptive behaviors or disease states, including obesity (Bickel et al., 2012, 2019); thus, delay discounting has been identified as a potential therapeutic target for lifestyle related diseases, including prediabetes and T2DM (Epstein et al., 2019).

At least six systematic reviews or meta-analyses have examined the relationship between delay discounting and obesity (Amlung et al., 2016; Barlow et al., 2016; Bickel et al., 2021; McClelland et al., 2016; Sweeney & Culcea, 2017; Tang et al., 2019). Generally, these reviews include many of the same studies, and overall indicate that higher rates of delay discounting are correlated with higher rates of obesity. However, the average strength of the correlations between delay discounting and obesity were found to be small (Sweeny & Culcea, 2017) or medium (Amlung et al., 2016; Barlow et al., 2016), while some mixed or conflicting results were also observed (McClelland et al., 2016; Tang et al., 2019). Regarding these mixed results, Tang et al. (2019) argue that methodological heterogeneity resulted from studies measuring delay discounting using hypothetical rewards and the assumption that individual discounting behaviors will be appropriately modeled using Mazur's hyperbolic equation. However, when including these characteristics as moderates in the meta-regression, the effect of incentive-compatible delay discounting methods and atheoretical measures of delay discounting was not significant.

A comprehensive examination of the relationship between delay discounting and obesity can be found in Bickel et al. (2021), in which the authors systematically review the evidence for considering delay discounting as a candidate behavioral biomarker of obesity. The authors examine this relationship in five contexts (reviewed below) relevant to the identification of a biomarker: identifying individuals at risk for developing obesity, diagnosing obesity, measuring disease progression, predicting treatment outcomes, and measuring treatment efficacy.

Risk for Developing Obesity

No studies have assessed if increased delay discounting increases the likelihood of developing obesity in adults; however, studies examining the relationship between sensitivity to delayed rewards and the onset of obesity have been assessed in children. As delay discounting can be methodologically difficult to assess in children, the majority of studies measure delay of gratification, a construct that is similar but not identical to delay discounting. At least seven studies have observed longitudinal associations between a reduced ability to delay gratification and increased weight. However, it is unknown how measures of delay discounting in young adults or older children collected longitudinally would predict development of obesity.

In adults, high rates of delay discounting are correlated with increased food consumption and reduced levels of physical activity, contributing to excess adiposity (Appelhans et al., 2012; Sofis et al., 2017). Specifically, increased delay discounting is associated with increased consumption of fast food, high sugar foods, and reduced overall dietary quality. In some studies, delay discounting moderates the relationship between food consumption and other variables; for example, the relative reinforcing value of food predicted caloric intake, with higher rates of discounting leading to greater caloric intake (Rollins et al., 2010). One meta-analysis found that steeper discounting is related to decreased rates of physical activity in adults (Sweeney & Culcea, 2017). Overall, there is a large body of evidence linking high rates of delay discounting to reduced physical activity and increased food consumption in the laboratory and natural environment in adults, although the evidence for a similar link in children is mixed. Future work should investigate the relationship between delay discounting and exercise valuation in individuals with obesity.

Diagnosing Obesity

The ability of delay discounting to distinguish between obese and non-obese individuals has been observed across a wide range of studies, although there have been a number of null findings in which no association was observed between delay discounting and BMI. There are methodological concerns regarding studies reporting significant associations and studies reporting null findings, although Bickel et al. (2021) note that a smaller proportion of the studies reporting significant associations are subject to these methodological concerns compared with the proportion of the studies reporting null findings. The methodological concerns include using small amounts of money in the discounting task, sampling obese individuals seeking to lose weight (which may be related to delay discounting), and including a small range of BMI in recruited samples. Additionally, delay discounting has not been found to measure the severity of obesity, suggesting that while delay discounting may be associated with obesity, it may not be predictive of BMI values beyond 30. Importantly, only four studies have attempted to examine this relationship, and did so only in females or in age ranges excluding individuals over 50. Future research should extend these methods to more diverse samples.

Measuring Disease Progression

In order to assess whether delay discounting is able to predict weight gain and subsequent obesity (i.e., measuring disease progression), longitudinal measurements of temporal discounting and BMI are required; unfortunately, only two studies have examined this relationship. One study found that change in delay discounting predicted weight gain over time, while the second found that change in delay discounting did not predict weight gain over time. In the study with null findings, weight gain or BMI changes either were not observed in a large number of participants or reflected only small changes, limiting the ability for a relationship to be detected.

At present, this dearth of research is a critical gap in our understanding of the relationship between changes in delay discounting and weight gain.

Predicting Treatment

Similarly, few studies have examined the ability of delay discounting to predict the success of behavioral treatments for obesity, finding mixed results. Two studies, one in adults and one in children between the ages of 7 and 12, found that baseline discounting was associated with weight change over the course of the intervention, albeit in different directions. Children with higher baseline discounting rates lost less weight than children with less steep discounting; in the study including only adults, participants in the active condition of the treatment study with higher baseline discounting rates lost more weight than the control condition. It is possible that the active condition was more effective for individuals with higher discounting, suggesting that treatment type may moderate the ability of delay discounting to predict treatment effectiveness. This area is another gap in knowledge regarding delay discounting and obesity.

Treatment Effectiveness

The ability of delay discounting to measure the effectiveness of treatment for obesity is the final point of discussion in the review. If rates of delay discounting change as weight loss occurs, then discounting may function as a measure for identifying efficacious interventions. Discounting has been shown to be modifiable in obese individuals; episodic future thinking (EFT) is one method that has recently received increasing interest with regards to reducing delay discounting in this population. Of the eleven studies utilizing EFT, eight were found to have positive effects on delay discounting and behaviors related to obesity. The heterogeneity of methods to generate and implement EFT cues complicates the analysis of this intervention's utility. Additionally, the impact of weight loss or physical interventions on delay discounting is an area lacking in research, with published studies having substantial differences in methods. Initial data suggests that delay discounting may change as a result of behavioral interventions for weight loss or physical activity, but more research is needed, especially research including long-term measurements of weight loss and/or maintenance.

Summary

Generally, steep discounting of money and food rewards is associated with higher BMI values, although the heterogeneous nature of delay discounting tasks and analysis methods complicates interpretations. Overall, the literature suggests a small but significant association between delay discounting and obesity; however, the directionality of this relationship has yet to be ascertained. Notably, no longitudinal studies have been conducted examining the relationship between delay discounting and likelihood of developing obesity in young adults and adolescents. The lack of research demonstrating elevated rates of delay discounting preceding the development of obesity warrant caution when making statements regarding causality.

Delay Discounting and Type 2 Diabetes

Compared to obesity, less is known regarding the relationship between delay discounting and type 2 diabetes. The majority of work examining this relationship has been cross sectional, with one study combining cross-sectional data with registry data. Madsen et al. (2019) performed a systematic review examining time preferences and self-management behaviors in individuals with diabetes (both type 1 and type 2). The authors included studies that measured time preferences (either using continuous measures generated by delay discounting tasks or ordinal measures generated by questionnaires) and measures of diabetes outcomes. In this section, we will review the studies identified by Madsen et al. (2019) that sampled individuals with T2DM. Finally, we will review any studies published following the systematic review.

Reach et al. (2011) used a cross sectional study design to examine the association between present biasedness and diabetes control behaviors in 90 patients of a health clinic with type 2 diabetes. Researchers measured present bias by asking participants to indicate their preference for 500 euros immediately, 800 euros in six months, or 1500 euros in one year; those who selected the 500 or 800 euros were considered present biased, while those who selected 1500 euros in one year were not considered present biased. Present biasedness was found to significantly predict HbA1c values above 7.0% using logistic regression; however, transforming HbA1c from a continuous variable to a dichotomous variable decreases the resolution of the measure, making logistic regression an inappropriate choice. Additionally, the method to assess present bias was also reduced from a three point ordinal scale to a dichotomous variable, further reducing the resolution of the predictor variable. Future research should utilize higher resolution measures of present bias (e.g., delay discounting) and retain the continuous distribution of HbA1c; indeed, this would be done in 2016 by Lebeau and colleagues.

Lebeau et al. (2016) describe a cross sectional comparison of delay discounting and HbA1c in 93 adults with type 2 diabetes. Participants completed adjusting amount delay discounting tasks for hypothetical monetary gains and losses, while HbA1c was measured the day of the survey or within the last week. Researchers observed a positive correlation between high rates of discounting for gains and HbA1c; this correlation remained significant after adjusting for confounding variables (i.e., age, BMI, diabetes duration, etc.). No association between discounting for losses and HbA1c was observed. This study strengthens the conclusions of Reach et al. (2011) due to methodological improvements, but is still unable to identify delay discounting as a causal factor in the etiology of type 2 diabetes.

Mørkbak et al. (2017) combined data from a postal survey and registry on a sample of 79 adults with type 2 diabetes, allowing for a longitudinal examination of present bias with age of onset and disease progression in T2DM. Researchers noted that individuals who have been living with chronic illness for longer periods of time may have experienced a shift in present bias due to the disease, and therefore controlled for duration of disease diagnosis and other socioeconomic variables in their analyses. Present biasedness was found to be a significant predictor for age of onset for T2DM, and this effect was stronger in individuals diagnosed before 48 years of age. Additionally, increased rates of present bias was associated with lower rates of physical exercise, diabetes literacy, quality of life, glycemic control, and higher rates of obesity. Overall, these results suggest that present biasedness may play a causal role in the onset of T2DM and less effective disease management. Importantly, the study design prevents a firm conclusion of causality; instead, the results support reduced confidence in reverse causality as described above.

Reach et al. (2018) recruited 120 hospitalized patients with type 2 diabetes to examine the role of disruption in time projection on medication adherence using a cross-sectional survey. To measure disruption in time projection, the authors utilized questionnaires and tasks to assess patience, temporal horizon (defined as the ability to imagine future events), and the subjective level of physical sameness between the current self and future selves. To measure patience, the authors asked participants to indicate their preference between 500 euros today or 1500 euros one year from now. Temporal horizon was measured in two ways: 1) by asking participants to list possible personal future events and measuring the maximal future temporal distance described, and 2) by having participants complete a narrative of a person thinking of the future and measuring the temporal distance written in the narrative. Participants who chose 500 euros today had significantly higher odds of having a recent HbA1c value of greater than 8%, while participants with longer temporal horizons had lower odds of HbA1c greater than 8%. These findings add further credence to the previously observed link between delay discounting and T2DM. Furthermore, the finding linking the concept of the “temporal horizon” with HbA1c and medication adherence is novel.

In a similar cross-sectional survey, Reach, Pellan, et al. (2018) obtained data from 1214 individuals with T2DM using a mail survey of French adults. Researchers measured medication adherence, demographics, clinical outcomes related to diabetes, and psychosocial variables (e.g., delay discounting, temporal horizon). In univariate analyses, delay discounting rates were not found to be significantly associated with medication adherence. Using multivariate linear regression, higher rates of delay discounting were significantly associated with lower rates of medication adherence; however, the measures of medication adherence and delay discounting were not coded as continuous variables, reducing the appropriateness of linear regression for these variables. The authors did not report associations between delay discounting and HbA1c or other clinical outcomes related to T2DM.

Karl et al. (2018) analyzed data from a cross-sectional survey of 655 German adults with T2DM. The survey included measures of diabetes related self-management, time preference between immediate rewards and future health (i.e., discounting of delayed health outcomes), and outcome expectancy (i.e., belief that appropriate diet and exercise self-management would lead to improved disease outcomes). Individuals with higher time preferences (i.e., those who value immediate rewards over future health) were found to engage in reduced rates of diabetes self-management behaviors. Individuals with higher outcome expectancy (i.e., those who agree that diet and exercise self-management can lead to improved T2DM outcomes) were found to engage in higher rates of diabetes self-management behaviors. An interaction model indicated that individuals with low time preference engaged in higher rates of self-management when they also had high outcome expectancy.

Finally, Campbell et al. (2021) examined the relationship between delay discounting, delay aversion, and diabetes self-management behaviors using a cross-sectional study of 356 adults with T2DM. Delay discounting and delay aversion (described by the authors as valuation of the future and negative emotions related to experiencing a delay, respectively) were measured using a questionnaire. Outcomes and self-management behaviors included HbA1c, dietary patterns, exercise, blood glucose testing, foot care, and both physical and mental quality of life. Delay discounting was found to be negatively associated with dietary patterns and foot care, but not HbA1c. Similarly, delay aversion was negatively associated with dietary patterns, foot care, and mental quality of life, but not HbA1c.

Summary

Overall, the evidence linking delay discounting with T2DM disease onset, self-management behaviors, or disease outcomes are overwhelmingly cross-sectional associations (with the exception of Mørkbak et al. 2017), preventing firm conclusions of a causal relationship between higher rates of delay discounting and worse T2DM related outcomes. However, the cross-sectional relationship appears to be robust with regards to differences in measurement of delay discounting (often conceptualized as present bias or time preference in economic literature) and differences in measurement of T2DM disease severity, self-management behaviors, and outcomes. This robustness suggests that the relationship between delay discounting and T2DM self-management behaviors and outcomes is not an artifact of measurement methodologies. While more work is needed to establish causality, this body of literature suggests that delay discounting (i.e., present bias or time preference) could be a putative target in interventions to improve T2DM disease progression and outcomes.

Delay Discounting and Physical Activity

High rates of delay discounting are associated with reduced rates of physical activity and exercise. In the meta-analysis reviewed in the Delay Discounting and Obesity section, Sweeney and Culcea (2017) included exercise as an outcome variable. Overall, higher rates of delay discounting were significantly associated with reduced rates of physical activity, although the effect size was small and was not moderated by task type (i.e., delay discounting tasks or subjective questionnaires). Additionally, a number of studies not fitting the inclusion criteria for the aforementioned meta-analysis or published later have also observed that preferences for immediate rewards and higher rates of present bias are associated with reduced rates of physical activity or physical activity maintenance (e.g., Avraham et al., 2020; Eberth et al., 2022; Kosteas, 2015; Leonard et al., 2013; Shuval et al., 2017).

In a cross-sectional study of 143 nurses, Avraham et al. (2020) observed a significant negative relationship between higher rates of delay discounting and lower intentions to engage in or rates of planning for physical activity, but did not observe a significant relationship between delay discounting and self-reported physical activity. Eberth et al. (2022) used a large, nationally representative longitudinal data set (National Longitudinal Surveys of Youth 1979) to examine the relationship between present bias and physical activity initiation and maintenance, finding that higher rates of present biases were associated with failing to maintenance physical activity habits, but not with physical activity initiation. Using the same longitudinal cohort, Kosteas (2015) examined the relationship between time preference and physical activity and found that both men and women with greater present bias (measured by asking participants how much money they would save after an unexpected windfall) engage in less physical activity. Leonard et al. (2013) obtained cross sectional data from 169 low-income minorities, including delay discounting experiments with potentially real rewards and physical activity stages of change. Participants who were more likely to wait for larger but delayed rewards were more likely to report an advanced physical activity stage. Finally, in a large cross section sample of 7071 adults, Shuval et al. (2017) observed that individuals who were willing to wait longer for a hypothetical monetary reward were 1.2 times more likely to meet physical activity guidelines (measured using self-report).

Additional studies using higher resolution, serial binary choice delay discounting tasks (e.g., adjusting amount, monetary choice questionnaire) have observed similar relationships between delay discounting and physical activity (Daugherty & Brase, 2010; Hunter et al., 2018; LeComte et al., 2020; Tate et al., 2015). Daugherty and Brase (2010) examined the relationship between delay discounting, time perspective and a range of healthy behaviors (including physical activity) in 467 undergraduates. Using stepwise hierarchical linear regression, including measures of time perspective and delay discounting at step two significantly increased the variance in exercise behaviors accounted for by the model beyond step one (sex and Big Five personality scores). However, the variance in exercise behaviors independently accounted for by delay discounting was not significant; additionally, delay discounting was not correlated with exercise behaviors. Hunter et al. (2018) examined delay discounting and physical activity in 176 employees participating in a physical activity intervention, finding that participants with steeper rates of delay discounting reported less physical activity, even after controlling for socio-demographic variables. LeComte et al. (2020) found that delay discounting predicted self-reported physical activity during a typical week in 45 undergraduate students (lower rates of discounting were significantly correlated with higher rates of physical activity). Tate et al. (2015) examined delayed discounting and physical activity in a cross-sectional sample of 137 older adults, finding that older adults who engaged in physical activity had lower rates of delay discounting compared to older physically inactive older adults.

Physical activity as an intervention has been demonstrated to change delay discounting, while delay discounting has been found to moderate the effectiveness of using financial incentives to increase physical activity (Phillips et al., 2020; Sofis et al., 2017; Zhao et al., 2020). Sofis et al. (2017) examined changes in delay discounting following participation in a physical activity intervention designed to increase daily step counts. Attending more intervention sessions (walking) and experiencing greater walking pace improvement over seven weeks was correlated with decreased rates of delay discounting. In individuals with methamphetamine use disorder, Zhao et al. (2020) observed that participants who engaged in regular moderate-intensity exercise over twelve weeks showed decreased rates of delay discounting compared to controls (although this effect was not observed in participants engaging in high-intensity exercise). Finally, Phillips et al. (2020) examined how delay discounting rates moderate the effectiveness of financial incentives to increase physical activity. Participants with higher rates of delay discounting experienced larger declines in physical activity during the intervention, suggesting that the intervention was less effective in this group.

Summary

In summary, there is a consistent relationship between delay discounting and physical activity, indicating that individuals with lower rates of delay discounting tend to engage in increased rates of physical activity. Similar to findings regarding obesity and T2DM, the majority of work in this domain is cross sectional, and unable to establish causality. Participants with higher rates of delay discounting tend to engage in less physical activity than those with lower rates of delay discounting. Certain physical activity interventions may reduce delay discounting, and delay discounting may moderate the effectiveness of certain physical activity interventions. While the correlational data linking delay discounting and low rates of physical activity suggest delay discounting as a therapeutic target to increase physical activity, the research demonstrating reductions in delay discounting following physical activity interventions complicates this interpretation. It is possible that the relationship is bidirectional: changes in delay discounting mediates changes in physical activity, and vice versa. However, the focus of this dissertation is to examine one side of this potentially bidirectional relationship; namely, the effects of changes in delay discounting on physical activity.

Episodic Future Thinking

Episodic future thinking is the imagination of personal future events (Atance & O'Neill, 2001). As described in the Episodic Future Thinking section of chapter 1, EFT has been demonstrated to reduce delay discounting and behavioral outcomes relevant to physical health, including caloric consumption, demand for high calorie foods, and medication adherence in individuals with T2DM (Athamneh et al., 2020; Epstein, Jimenez-Knight, et al., 2022; Yang et al., 2019). Recently, work has been conducted to explore the feasibility of longer-term, repeated exposure to EFT cues, in both the laboratory and naturalistic settings (Athamneh et al., 2021; Epstein, Paluch, et al., 2022; Mellis et al., 2019; Sze et al., 2015). Longer-term clinical interventions have translated the use of EFT from acute, single-session exposures to experiments including repeated cue generation and multiple exposures. This translational work has important implications for control conditions in longer-term experiments.

Episodic Future Thinking and Health Behavior Change

The practice of evoking episodic future thinking to elicit changes in delay discounting was first reported by Peters and Buchel (2010), who demonstrated that engagement in EFT reduced rates of delay discounting. The effect was a result of increased neural valuation signals in the anterior cingulate cortex, as well as increased neural coupling between the anterior cingulate cortex, hippocampus, and amygdala. The behavioral findings have been replicated across a broad range of populations, delay discounting tasks, and EFT tasks (Rösch et al., 2021; Rung & Madden, 2018). Additionally, EFT has been shown to impact other behavioral outcomes relevant to health. Yang et al. (2019) conducted a meta-analysis examining the effect of cognitive strategies on weight loss and eating behavior. When analyzing the effect of solely EFT on eating behavior (nine studies; n = 432), the authors observed a significant medium effect (g = .708, 95% CI = 0.22 - 1.19) of EFT on eating behavior (i.e., decreased caloric intake).

Additional research examining the effects of EFT on caloric intake or other health behaviors related to food intake has since been published. Chang et al. (2020) examined the effects of EFT on consumption of lower energy dense food (muesli) and higher energy dense food (Maltesers), finding that in individuals with obesity, engagement in EFT led to reduced consumption of Maltesers but no differences in muesli consumption. Athamneh et al. (2020) examined the effect of EFT (including health-goal oriented EFT) on demand for fast food and cravings in individuals with obesity. Participants engaging in health-goal oriented EFT and standard EFT had reduced intensity of demand compared to ERT participants. Additionally, participants who engaged in health-goal oriented EFT had increased demand elasticity (i.e., higher rates of reduced consumption as a function of increasing price) and reduced craving for fast food compared to ERT participants. Hollis-Hansen et al. (2020) designed an experiment in which mothers with overweight engaged in EFT or a control thinking condition before weekly grocery shopping for their families. EFT participants purchased less calories, less fat and saturated fat, and less sodium than control participants. Sze et al. (2015) conducted a small trial to examine the effect and feasibility of repeated EFT combined with a dietary intervention on weight loss and consumption of high- and low-energy density foods in parent-child dyads. The intervention was rated as easy to use and helpful by participants; despite the small sample size, adults randomized to the EFT condition lost more weight than control participants. No changes were observed regarding consumption of high- and low-energy density foods. Sze et al. (2017) examined the effects of acute EFT on delay discounting and operant behavioral economic demand for fast food in an online sample of people with obesity. Compared to ERT and no episodic thinking control participants, EFT participants had significantly lower rates of delay discounting and lower demand for fast food.

Not all work in this area suggests that EFT may reduce caloric consumption, behavioral economic measures of value, or food choices. (Mansouri et al., 2020) recruited participants with overweight or obesity for an experiment examining the effects of repeated engagement in EFT (i.e., thrice per day over one week) on delay discounting, the relative reinforcing value of low- and high-energy dense foods, and caloric consumption during a contrived ad libitum eating task. Compared to ERT participants, EFT participants did not have reduced delay discounting, consume less calories during the ad libitum eating task, or have a lower relative reinforcing value of high-energy dense foods. Indeed, EFT participants consumed more calories during the second ab libitum eating task compared to the baseline session. Segovia et al. (2020) designed an experiment in which participants with normal weight, overweight, or obesity either engaged in EFT (via viewing weight-increased avatars of themselves), received health information, or participated in an inactive control (i.e., waiting two minutes). Afterwards, participants completed a task in which they chose between two snacks: a regular version and a “lite” version containing fewer calories. Participants with overweight or obesity in the health information condition chose more lite snacks compared to EFT and control participants. Stein et al. (2020) conducted an in-lab replication of Sze et al. (2017), examining the effects of EFT on delay discounting and operant behavioral economic demand for fast food in adults at risk for T2DM. While engagement in EFT did decrease delay discounting, no effects were observed on demand for fast food in this replication.

Presently, the effects of EFT on physical activity, exercise, or behavioral economic measures of exercise valuation are unknown. Only one study has examined the effects of regular engagement in EFT on clinically meaningful outcomes for individuals with prediabetes (e.g., BMI, HbA1c) including physical activity as a secondary outcome (Epstein et al., 2022). The authors conducted a 24-week randomized controlled trial examining the effects of EFT combined with a weight loss intervention for overweight adults with prediabetes; participants receiving regular engagement and instruction on using EFT did not lose more weight, improve HbA1c, or increase objectively measured physical activity relative to controls, despite significant differences in delay discounting (Epstein et al., 2022). Additionally, at least one registered report has been published describing the rationale and design of an experiment to test the effects of EFT on delay discounting, weight loss maintenance, and physical activity following a behavioral weight loss intervention (Leahey et al., 2020), although the findings from this study await publication of the final report.

Control Conditions in EFT

The purpose of control conditions in EFT invention studies is to reduce the probability of a confounding variable influencing the dependent variable, thereby increasing internal validity.

A range of control conditions have been used in acute laboratory settings (e.g., episodic recent thinking, standardized episodic thinking, semantic future thinking); however, these controls have significant shortcomings when used in long-term clinical settings (Chiou & Wu, 2017; Hollis-Hansen et al., 2019; Rung & Epstein, 2020). For example, episodic recent thinking (ERT) involves generating personalized (i.e., episodic) cues based on recently experienced events, controlling for episodicity and the act of cue generation. In order to keep ERT cues "up to date" in clinical trials involving repeated cue generation, cues with recent temporal proximity (e.g., 12 hours, 1 day) would have to be regenerated prohibitively often. This frequency of regeneration would need to be matched in the EFT group, which could be challenging for participants to generate novel, detailed future experiences. Additionally, the concern of ERT inadvertently causing prospective thought may increase as participants engage in ERT regularly (Hollis-Hansen et al., 2019). Finally, ERT as a clinical control fails to hold constant participants' expectation of improvement or perceived helpfulness between ERT and EFT groups. (Rung & Epstein, 2020) describe a novel clinical control condition, Health Information Thinking (HIT), in which participants read and respond to health-information vignettes and generate cues by describing their reaction to the health-information vignettes. HIT was developed as a control specifically to address these concerns and was not found to decrease delay discounting relative to EFT in a healthy sample using general health information vignettes. However, it is unknown how the HIT control condition will affect delay discounting in physically inactive individuals or individuals with obesity and type 2 diabetes when health-information vignettes contain information directly relevant to physical activity or diabetes management, respectively.

Summary

Episodic future thinking involves mental time travel to personally relevant potential futures. Studies examining the effect of EFT on delay discounting or health behaviors may involve acute (i.e., single) exposures or repeated exposures; these different experimental arrangements require different control conditions. EFT tends to reduce caloric intake and behavioral economic measures of food valuation, although some studies have observed null effects. One study tested the effect of EFT on physical activity within the context of a weight loss and prediabetes intervention but did not find that EFT increased physical activity. These results suggest that more basic experimental work is needed to understand the relationship between EFT and physical activity before successful translation of the intervention is likely.

Conclusion

This literature review highlighted the following gaps in scientific knowledge: the current limitations of behavioral economic methods to measure the value of exercise and the need to understand exercise valuation relative to free time, the unknown effect of EFT on the value of exercise and delay discounting in adults who are not meeting physical activity guidelines, and the unknown effect of EFT on the value of exercise, delay discounting, and self-reported physical activity in adults with T2DM and obesity participating in a clinical trial.

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Measuring behavioral economic demand for exercise: Development of the leisure-time-as-price hypothetical exercise purchase task

Abstract

Physical inactivity is a major contributor to increased disease prevalence and reduced quality of life. Measuring behavioral economic demand for exercise may enable more effective physical activity intervention development. We present the leisure-time-as-price exercise purchase task (LT-EPT), wherein respondents indicate likelihood to trade leisure time for access to exercise time. In an online experiment, 175 adults completed the LT-EPT, yielding measures of alpha (α; rate of change in elasticity), breakpoint (BP_1; the highest price at which participants traded leisure time for exercise), P_{max} (the price with highest leisure time expenditure), and $Q_{1\%}$ (likelihood of exercise at the lowest price). Additionally, participants completed measures hypothesized to be related to exercise demand (e.g., self-reported physical activity). Hypothetical likelihood of exercise decreased with increasing leisure time costs; data were generally well described by the exponentiated model of demand (median R^2 = .87). Alpha was negatively correlated with self-reported physical activity measures (ρ = -.26 to -.39), while BP_1, P_{max}, and $Q_{1\%}$ were positively correlated (ρ = .11 to .36). The LT-EPT may be more appropriate for the measurement of exercise demand than methods using monetary costs, as this novel method uses a more ecologically valid conceptualization of exercise costs (i.e., time).

Keywords: exercise demand, operant behavioral economics, hypothetical purchase task, humans

Introduction

Physical inactivity is a major contributor to negative health outcomes in the United States. Approximately 8.3% of premature deaths can be attributed to physical inactivity; inactive adults incur an estimated 26.6% greater healthcare expenditures than active adults (Carlson, 2018; Carlson et al., 2015). Despite considerable immediate and delayed health benefits associated with regular physical activity, only 24.2% of American adults in 2020 were meeting the Physical Activity Guidelines for Americans (Elgaddal, 2022; Piercy et al., 2018). While there are many existing efficacious behavioral interventions to increase physical activity (e.g., contingency management; Howlett et al., 2019; Olander et al., 2013), wider efforts to improve physical activity intervention development or delivery may benefit from conceptualizing exercise (i.e., planned physical activity done to improve or maintain fitness; Caspersen et al., 1985) as a reinforcer, wherein reinforcing value is one of many components influencing the choice to engage in exercise or sedentary behaviors (Flack et al., 2017, 2019b). Indeed, at least one randomized controlled trial has demonstrated that engaging in regular exercise can increase the reinforcing value of exercise in sedentary adults (Flack et al., 2019a). Thus, improving our measurement of the reinforcing value of exercise could lead to valuable insights regarding behavioral characteristics of individuals with varying valuation for exercise, and help to identify interventions that may increase the valuation of exercise and lead to increased rates of physical activity (Carr & Epstein, 2020).

At present, two common operant behavioral economic approaches have been used to examine reinforcing value—relative reinforcing efficacy and economic demand (Hursh & Silberberg, 2008). However, approaches to measuring the reinforcing value of exercise using either paradigm have important limitations related to construct validity and generalizability.

Relative reinforcing efficacy may be determined by arranging a concurrent choice procedure, in which participants can work to gain access to two reinforcers (e.g., five minutes of sedentary activity vs. five minutes of physical activity). Participants are able to engage in an operant response (e.g., mouse button clicks) to meet the active schedule of reinforcement for a given reinforcer (e.g., 2 clicks); afterwards, the schedule escalates, increasing the number of responses required to gain access to the reinforcer (e.g., 4 clicks). In this arrangement, participants must choose the option to which they allocate behavior and earn the associated reward. The largest schedule requirement met on a given option is termed breakpoint and is considered a measure of reinforcing value (Hodos & Kalman, 1963). However, as breakpoint is assessed for two reinforcers in the context of a concurrent choice procedure, the measure of reinforcing value is relative between the reinforcers. As such, relative reinforcing efficacy of exercise paradigms do not fully reflect decision making in the natural environment, wherein individuals may choose between engaging in exercise or other alternative behaviors (some of which can occur simultaneously, e.g., eating ice cream while watching TV). Additionally, preference between two commodities may be moderated by schedule requirements to obtain each commodity; preference for a commodity relative to another may shift as the price to obtain each commodity increases (Bickel & Madden, 1999; see Johnson & Bickel, 2006 for an in-depth discussion on the limitations of relative reinforcing efficacy). Despite these limitations, relative reinforcing efficacy is useful for measuring the reinforcing value of exercise, with higher levels of relative reinforcing value for aerobic exercise and resistance exercise being predictive of meeting physical activity guidelines for their respective modes of exercise (Flack et al., 2017).

Similar to relative reinforcing efficacy, demand is assessed using an experimental arrangement in which subjects must meet a specific schedule of reinforcement to obtain the commodity across escalating unit prices (i.e., response requirement for one unit of the commodity (Hursh, 1980). One such arrangement–the purchase task–enables assessment of demand across a broad range of commodities, including drugs of abuse, obesogenic foods, and public transportation (Epstein et al., 2018; Hack et al., 2023; Jacobs & Bickel, 1999). Purchase tasks may utilize real or hypothetical response requirements or rewards, with evidence indicating correspondence between demand for hypothetical and actual rewards (Amlung et al., 2012; Amlung & MacKillop, 2015). Using the purchase task framework, subjects report the units of a commodity they would purchase across a range of unit prices (i.e., quantity purchase tasks; Jacobs & Bickel, 1999; MacKillop et al., 2008); similarly, subjects may report the likelihood of purchasing one unit of a commodity across a range of prices (probability of single purchase tasks; Reed et al., 2016; Roma et al., 2016). Across versions subjects are instructed to make their purchases as if certain constraints were in place; for example, that their income and savings are unchanged, that the commodity must be consumed within a specific time period, that the commodity may not be shared or sold, or that their only access to the commodity is restricted to what they purchase in the task. The assumption regarding participants' income and savings allows the task to more closely approximate the real-world conditions under which economic decisions take place, potentially increasing external validity. While the demand paradigm has proven valuable to increase our understanding of economic decision making (Roma et al., 2017), previous attempts to apply this paradigm to the reinforcing value of exercise face serious conceptual limitations.

To date, two hypothetical purchase tasks have been developed to estimate demand for exercise: the gym membership purchase task (GMPT) and the exercise purchase task (EPT) (Brown et al., 2021; May, 2020; Weinsztok et al., 2023). In two versions of the GMPT, participants report the probability of purchasing a monthly gym membership or the quantity of one-day passes they would purchase across a range of prices. However, demand for gym membership may not represent demand for exercise for a large segment of the population who may find gyms to be aversive or prefer other forms of exercise (e.g., hiking, skiing, cycling), limiting the generalizability of the task. Indeed, in the probability-based version of the GMPT, demand for gym membership was not significantly correlated with self-reported minutes spent exercising outside of a gym or fitness center (Brown et al., 2021). This correlation was significant in the quantity-based version of the GMPT, but small in magnitude (ρ = .13). Together, these findings suggest that the GMPT may not capture demand for exercise for individuals who do not exercise in gyms or fitness centers.

In contrast, the EPT (May, 2020; Weinsztok et al., 2023) asks participants to purchase a discrete amount of exercise (e.g., 30 minutes) across increasing monetary prices. Importantly, the EPT overcomes the limitations of the GMPT by commodifying exercise itself, but lacks face validity as most exercises performed outside of a gym (e.g., running) incur no direct monetary costs. Moreover, conceptualizing the cost to engage in exercise as monetary does not reflect the experience of most individuals in developed nations, where lack of time is a barrier to physical activity (Farah et al., 2021; Koh et al., 2022). As noted by Theophrastus (370 BC - 285 BC), “Time is the most valuable thing a man can spend”. Time–typically leisure time–must be “spent” or allocated to engage in exercise.

In the present study, we developed a novel hypothetical purchase task to overcome the limitations associated with current methods to assess demand for exercise. In the leisure-time-as-price exercise purchase task (LT-EPT), participants indicate their likelihood to “purchase” weekly exercise time by trading a percentage of their typical weekly leisure time. To establish construct validity (specifically, criterion validity) for the LT-EPT, we conducted an online experiment wherein participants completed the LT-EPT, followed by self-report measures hypothesized to be related to exercise valuation (e.g., physical activity, exercise patterns). We examined data quality (i.e., demand data adhering to the law of demand, comprehension of purchase task instructions) and how demand data generated from the LT-EPT were characterized by the exponentiated model of demand (Koffarnus et al., 2015). Additionally, we calculated exploratory (i.e., without type I error correction) correlations between demand indices and measures hypothesized to be related to exercise valuation. Finally, we discuss the implications and limitations of the LT-EPT, including modeling demand for a commodity with non-monetary costs and the exploratory nature of task development.

Methods

Participants

We recruited *n* = 403 participants on February 10th, 2023, using Prolific, an online recruitment platform (prolific.co; Peer et al., 2021). Participants were required to be residing in the US, fluent in English, and over 18 years of age; a total of 34,463 participants met these criteria and had completed a survey on Prolific in the last 90 days. Of the 403 participants who began the survey, 5 participants did not respond to the informed consent question; all remaining 398 participants chose to participate. Of the remaining 398 participants, 38 participants did not respond to the English fluency question (see procedure section), and a further 3 participants did not indicate English fluency. The remaining 357 participants were randomized to complete either the LT-EPT (n = 175) or GMPT (*n* = 182); all finished the survey. For the sake of brevity and to allow greater analytical focus on our primary aims (LT-EPT development and validations), we report only the results of participants randomized to complete the LT-EPT. LT-EPT participants' demographics are displayed in Table 1.

We conducted an *a priori* power analysis to compare correlations between demand indices generated using the LT-EPT and GMPT with measures hypothesized to be related to exercise valuation (i.e., Fisher's Z transformation); assuming a medium effect size (Q) and a power of 80%, we determined that 356 participants (178 per group) would be required to detect a significant difference in correlations between tasks at the 0.05 α using a two-tailed test. However, for the sake of clarity, we do not report the results of these analyses. Thus, we conducted post hoc power analyses to determine our power to detect significant Spearman correlations between LT-EPT demand indices and measures hypothesized to be related to exercise valuation. The power corresponding with each correlation is depicted in the supplementary materials.

Procedure

This research was approved by the IRB affiliated with the first author's institution. The experiment was conducted using Qualtrics survey software. Participants provided informed consent by reading an IRB-approved consent information sheet and indicating their agreement; acquiring written informed consent was waived by the IRB. Participants then selected languages in which they were fluent from a list of 86 common languages; participants had to select English in order to continue. Participants then reported typical weekly leisure time, followed by random assignment to complete the LT-EPT or GMPT. Afterwards, participants completed a series of questionnaires; for the sake of brevity, we present only data generated from self-reported exercise and leisure time habits, or validated measures of physical activity enjoyment or self-reported physical activity. Specifically, participants self-reported minutes spent exercising inside of and outside of a gym or fitness center in a typical week, then completed the Physical Activity Enjoyment Scale - Short Version (PACES-S; Chen et al., 2021), the Godin-Shephard Leisure-Time Physical Activity Questionnaire (GSLTPAQ; Godin, 2011) and the International Physical Activity Questionnaire - Short Form (IPAQ-SF; Lee et al., 2011). Finally, participants reported demographic information. Participants were compensated $3; the median survey completion time was 11 minutes and 50 seconds, yielding an hourly compensation rate of about $15. The full version of all questionnaires and tasks can be viewed in the survey export, found in the supplementary materials.

Weekly Leisure Time

To self-report weekly leisure time, participants indicated the amount of time they have on both typical weekdays and weekend days separately, in hours. We defined leisure time as time spent engaging in recreational exercise, relaxing, watching television, socializing, spending time with family or friends, or engaging in hobbies. We instructed participants not to include time spent sleeping, working, in school, performing household chores, cooking meals, or commuting. We specified that recreational exercise would only include exercise performed for the sake of exercise, and not exercise that occurs while commuting or for transportation. This approach to measuring leisure time has not been validated.

Leisure-time-as-cost Exercise Purchase Task (LT-EPT)

In the LT-EPT, participants indicated their likelihood of giving up a percentage of their typical weekly leisure time in order to allocate that time to weekly exercise. Participants were instructed to imagine a hypothetical scenario where the only way they could engage in recreation exercise during the week is by sacrificing part of their weekly leisure time. The description of the hypothetical scenario was designed to control for preferences in the commodity (i.e., participants could engage in any form of exercise they desire during their purchased exercise time) and to create a closed economy (i.e., participants had no other access to exercise time except by purchasing it via leisure time). Additionally, we specified that the hypothetical exercise time could be "consumed" throughout the week. Likelihood was reported using a sliding scale from 0-100 with 5-unit increments. Participants indicated likelihood across a range of 18 ascending percentages of weekly leisure time (i.e., 1%, 2.5%, 5%, 7.5%, 10%, 12.5%, 15%, 17.5%, 20%, 22.5%, 25%, 30%, 35%, 45%, 50%, 60%, 75%, 100%). Due to a mistake in survey design, the 75% price was not limited to 5-unit increments; we retained participants' reported likelihood at this price, as opposed to rounding to the nearest 5-unit increment or otherwise altering the data. Each price was presented on a separate page of the survey in ascending order, with no option to regress within the survey (Tomlinson et al., 2023). We used participants' self-reported leisure time responses to calculate the amount of leisure time to be traded at each price. We displayed this information as hours and minutes of leisure time to trade each week and each day. For example, a participant reporting 2100 minutes of leisure time per week (300 minutes per day), would have been asked the following at the 1% price: "What is the likelihood that you would be willing to give up 1% [0 hours and 21 minutes] of your weekly leisure time to engage in the same amount of weekly recreational exercise? On average, this would be 0 hours and 3 minutes per day".

Participants answered a comprehension check question following the instructions but presented on the same page in the survey. The comprehension question stated, "Thanks for reading the instructions above. What will the following questions ask you to do?". Five answer choices were presented in random order: 1) "I will indicate the likelihood of giving up a *certain* amount of weekly *leisure time* for *half* as much weekly *exercise time*", 2) "I will indicate the likelihood of giving up *one day's* with of *leisure time* for *as much* weekly *exercise time*", 3) "I will indicate the likelihood of giving up a *certain* amount of weekly *exercise time* for as much weekly *leisure time*", 4) "I will indicate the likelihood of giving up a *certain* amount of weekly *leisure time* for *as much* weekly *sleeping time*", and 5) "I will indicate the likelihood of giving up a *certain* amount of weekly *leisure time* for *as much* weekly *exercise time*". Participants passed the comprehension check by selecting answer choice 5. After completing the comprehension check, the survey progressed to the purchase task; there were no consequences for answering the comprehension check correctly or incorrectly.

Physical Activity Enjoyment Scale - Short (PACES-S)

The PACES-S (Chen et al., 2021) is a shortened version of the Physical Activity Enjoyment Scale (Kendzierski & DeCarlo, 1991) and has been demonstrated in adolescents to be valid and reliable. Participants indicated their agreement with the following four statements in regard to the physical activity that they have been doing: "I enjoy it", "I find it pleasurable", "It is very pleasant", and "It feels good". Each item was rated using a bipolar scale from 1-5, with 1 indicating strongly disagree and 5 indicating strongly agree. A total PACES-S score (ranging from 4 to 20) was calculated by summing the ratings from each item.

Godin-Shepard Leisure Time Physical Activity Questionnaire (GSLTPAQ)

In the GSLTPAQ (Amireault et al., 2015; Godin, 2011), participants self-reported the average number of times they engage in at least 15 continuous minutes of strenuous physical activity, moderate physical activity, and mild activity during a typical week. To obtain a weekly leisure-time activity score, the values reported for only the strenuous and moderate category are multiplied by 9 and 5, respectively; the products are then summed. The GSLTPAQ has been validated in healthy adults (Amireault & Godin, 2015).

International Physical Activity Questionnaire - Short Form (IPAQ-SF)

In the IPAQ-SF (Lee et al., 2011), participants self-reported their typical weekly physical activity. Participants reported the typical amount of time spent engaged in: walking, moderate-intensity, vigorous-intensity, and sedentary activities. To calculate typical weekly MET-minutes, weekly walking minutes are multiplied by 3.3, weekly moderate-intensity minutes are multiplied by 4, and weekly vigorous-intensity minutes are multiplied by 8; these products are then summed. The IPAQ-SF has been validated using international samples (Craig et al., 2003). Using data collected from the IPAQ, we calculated the physical activity to leisure time ratio by dividing the sum of all self-reported physical activity (walking, moderate-and vigorous-intensity physical activity) time by self-reported leisure time.

Demographics and Other Participant Characteristics

Demographic questions included self-reported height and weight, education, income, gender, age, race, and ethnicity. Additionally, we asked questions about behavior related to typical exercise habits and exercise environments (Brown et al., 2021). Specifically, participants reported how many minutes they spend exercising at a gym, fitness center, or health center in a typical week. Relatedly, participants reported how many minutes they spend exercising outside of a gym, fitness center, or health center in a typical week. Using this data, we calculated the ratio of the sum of self-reported exercise (inside and outside of gyms, fitness centers, or health centers) to self-reported leisure time (i.e., exercise to leisure time ratio).

Data Analysis

Two-stage demand analyses

Using the two-stage demand analyses approach (Kaplan et al., 2021), each individual participant's demand data was fit to the exponentiated model of demand using a single nonlinear regression to estimate alpha (α; rate of change of elasticity). We present observed $Q_{1\%}$ (i.e., the likelihood of trading 1% of leisure time for exercise time) as the measure of intensity of demand rather than Q_0 (i.e., likelihood at zero cost) because interpretations of Q_0 are poorly defined in time-as-price probability purchase tasks (i.e., model-estimated Q_0 represents the probability of trading 0% of leisure time for 0% of exercise time). In addition, we observed measures of breakpoint (BP_1), the last price at which participants indicated any likelihood of purchase or trade, and P_{max}, the price at which maximum expenditure occurred. A k value of 1.898322 was used for the LT-EPT models; these values were obtained by subtracting the log10 of mean consumption at the lowest price from the log10 of mean consumption at the highest price, then adding 0.5 (Kaplan et al., 2019).

We did not fit models or include in analyses 38 participants who were flagged as providing nonsystematic consumption data, did not pass the purchase task comprehension check, or both (n = 10 nonsystematic but passed comprehension check, n = 18 failed comprehension check but systematic, and n = 10 failed comprehension check and nonsystematic; Stein et al., 2015). Additionally, responses that passed the task comprehension check and indicated zero consumption across all prices (i.e., no demand at any price) were included in subsequent analyses (n = 3); however, as this pattern of responding is unable to be fit using nonlinear regression, we assigned these individuals values of zero for all indices except α. Finally, a single individual did not report any leisure time during a typical week; additionally, this individual indicated a flat 100% likelihood of trading leisure time for exercise time across all prices. We did not include this individual's demand data in subsequent analyses as the LT–EPT prices are unable to iterate when a participant self-reports zero leisure time. In total, we did not obtain derived measures for 42 participants, and excluded observed measures for 39 participants.

Correlations between demand indices and other measures

Spearman's rank-order correlations were used to test if demand indices (*Q1%*, *α*, BP_1, and P_{max}) were correlated with measures hypothesized to be related to exercise valuation, including: BMI, age, exercise to leisure time ratio, physical activity to leisure time ratio, PACES-S score, GSLTPAQ score, and physical activity (weekly MET minutes). One participant provided incomplete GSLTPAQ data, preventing their GSLTPAQ data from being included in correlations with demand indices. Due to the inestimable *α* associated with zero demand responses and missing GSLTPAQ data, $n = 136$ for correlations between $Q_{1\%}$, BP_1, P_{max} and all other variables excluding GSLTPAQ, for which $n = 135$; $n = 133$ for correlations between *α* and all other variables excluding GSLTPAQ, for which $n = 132$. Correlations between demand indices and other measures only include indices generated by systematic consumption data and from individuals who correctly answered the purchase task comprehension check question.

All analyses were performed in R (version 4.2.1) using RStudio (Posit team, 2023; R Core Team, 2022). We used an *α* value of .05 for null-hypothesis significance testing; due to the exploratory nature of task development, we did not control for multiple comparisons. Data wrangling, shaping, cleaning, and visualizations were performed using the *tidyverse* collection of packages (Wickham et al., 2016, 2019). Table 1 was generated using the *gtsummary* package (Sjoberg et al., 2021). Demand analyses were performed using the *beezdemand* package (Kaplan et al., 2019). Spearman correlations were generated using the *apaTables* package (Stanley, 2021). The study and analysis plan were not preregistered.

Results

Demographic data are presented in Table 1. Individual-fits to the exponentiated model of demand for the LT-EPT (median $R^2 = .87$; IQR $R^2 = .81 - .92$) are depicted in Figure 1. Of the

175 participants who completed the LT-EPT, 20 participants (11.42%) generated nonsystematic data; 28 participants (16%) failed the comprehension question following the task instructions. Summary statistics (i.e., mean, standard deviation, median, and interquartile range) for demand indices ($Q_{1\%}$, α, BP_1, and P_{max}) are displayed in Table 2.

Spearman's correlations describing the rank-order associations between demand indices ($Q_{1\%}$, α, BP_1, and P_{max}) and measures hypothesized to be related to exercise valuation are depicted in Table 3. Complete correlation matrices can be found in the supplementary materials. Correlations were consistent with outcomes suggesting construct validity (e.g., lower α values and higher $Q_{1\%}$, BP_1, and P_{max} values were associated with higher ratios of self-reported exercise to leisure time and higher physical activity enjoyment).

Discussion

The present study describes initial steps in the development of the LT-EPT as an operant behavioral economic method to measure the reinforcing value of exercise. To our knowledge, the LT-EPT is the first hypothetical purchase task to conceptualize time as the sole cost to gain access to exercise, although previous work has examined the effect of delay on likelihood of monetary purchases or transportation decision making (Hack et al., 2023; Schwartz & Hursh, 2022). In this section, we discuss model fitting and data quality, followed by construct validity. Finally, we consider the interpretation of P_{max} and O_{max} for probability of purchase task using time as the price, limitations of this study, and future directions.

Results suggest that the LT-EPT is able to generate systematic data to estimate demand for exercise as a function of time costs. We observed 88.6% of demand data to be systematically affected by leisure time cost (i.e., in accordance with the law of demand). Nonetheless, 20 participants (11.4%) generated nonsystematic data, and 28 participants (16%) failed the comprehension check question following the task instructions (note that there may be overlap between these subsamples). In total, 38 participants (21.7%) failed one or both of these criteria. Although purchase task comprehension checks are infrequently used and comparisons between studies are confounded by recruiting from different platforms at different times, the observed rate of nonsystematic data approximates those seen in other tasks (e.g., Kaplan et al., 2017). We propose that the current iteration of the LT-EPT may involve unfamiliar estimations of hypothetical behavior or complex task instructions, potentially limiting the utility of the task and indicating the need for further refinement of task instructions.

We observed significant correlations between all demand indices and some measures hypothesized to be related to exercise demand, indicating support for construct validity by demonstrating criterion validity. BP_1, defined as the last price at which participants indicated any probability of trading leisure time for exercise time, and P_{max}, defined as the leisure time price (in units of percent of total weekly leisure time) corresponding with the greatest product of likelihood of consumption and leisure time price, was correlated with all measures included in Table 3 (ρ = -.18 – .36). Negative correlations were observed between BMI and age, suggesting that as individuals' BMI or age increases, willingness to trade higher percentages of leisure time for exercise time decreases. Positive correlations were observed between exercise to leisure time ratio, physical activity to leisure time ratio, PACES-S, GSLTPAQ, and weekly MET minutes. The exercise and physical activity to leisure time ratio variables represent the amount of time participants dedicate to exercise or physical activity relative to their total leisure time; higher ratios indicate allocating a larger proportion of available leisure time to exercise or physical activity. Positive correlations between these variables with breakpoint and P_{max} suggest that individuals who self-report allocating a larger ratio of exercise to leisure time, enjoy physical activity, and engage in more exercise or physical activity are more likely to be willing to trade higher percentages of their leisure time for exercise time. As the logic of the LT-EPT is based on trading leisure time for exercise, observing positive correlations between these measures with breakpoint and P_{max} is as we would expect.

Observed intensity of demand (i.e., $Q_{1\%}$), defined as the probability of trading 1% of leisure time for exercise time, was positively correlated with age, exercise to leisure time ratio, PACES-S, and GSLTPAQ (ρ = .18 – .32). While the interpretation of the latter three variables is consistent with the above interpretations (i.e., with breakpoint and P_{max}), here age is positively correlated with $Q_{1\%}$, suggesting that older individuals were more likely to report a higher probability of exercise when available at minimal cost despite decreased likelihood to trade higher percentages of leisure time for exercise time. Interestingly, the exercise to leisure time ratio correlation but not the physical activity to leisure time ratio correlation was significant. The exercise to leisure time ratio may be a better estimate of participants' inclination to trade leisure time for exercise time in the natural environment than the physical activity to leisure time ratio, as the latter variable captures all physical activity time, which includes nonvolitional activity. Thus, the exercise to leisure time ratio is more directly related to demand indices generated by the LT-EPT, which is specific to volitional exercise time.

The rate of change in elasticity (i.e., α) was correlated with all measures except age; a positive correlation was observed with BMI, and a negative correlation with all remaining measures (ρ = -.39 – .30). These results suggest that individuals with a higher BMI may be more sensitive to increases in prices to engage in exercise, particularly when the cost is reduced leisure time. In the LT-EPT, all leisure time traded for exercise time must be used to engage in exercise; a higher likelihood of making the trade at higher percentages (i.e., prices) of leisure time would require long bouts of daily exercise, which may be more physically challenging for individuals with obesity, who tend to engage in lower rates of physical activity (Cooper et al., 2000). The negative correlations between the remaining variables and α suggest that individuals who score highly on these measures have reduced sensitivity to increases in price. This is consistent with our conceptual understanding of demand assessed by the LT-EPT; individuals who self-report higher levels of exercise, physical activity, or enjoyment of physical activity are willing to defend consumption of exercise time despite increases in time costs.

Interpretation of P_{max} and O_{max} in the LT-EPT

The interpretation of P_{max} (and by extension, O_{max}) in the LT-EPT has important differences compared to monetary quantity purchase tasks and likelihood of purchase tasks. In monetary quantity purchase tasks, P_{max} represents the price at which the maximum monetary expenditure occurs; O_{max} represents the maximum monetary costs incurred (i.e., the product of price and units purchased). For likelihood of purchase tasks, interpretation at the individual level is altered (Roma et al., 2016). For example, if we observed a P_{max} of $50 but the participant reports a 50% likelihood of purchasing the commodity, the participant is reporting that they may either purchase the commodity at this price (thereby spending $50) or not purchase it (spending $0) at equal probability. For the individual, it is unclear if this P_{max} and likelihood of consumption corresponds with an O_{max} of $0 or $50. At the sample level, the average O_{max} will approach the product of P_{max} and the average proportional likelihood of purchase (e.g., $50 * 0.5). Extending this example to the LT-EPT, P_{max} represents the leisure time price (in units of percent of total weekly leisure time) corresponding with the greatest product of likelihood of consumption and leisure time price (i.e., O_{max}). At the individual level, LT-EPT O_{max} is subject to the same limitations of interpretation as other likelihood of purchase tasks; at the sample level, the average LT-EPT O_{max} will approach the product of P_{max} and the average likelihood of purchase at P_{max}. Thus, O_{max} may represent the average percentage of leisure time that will be traded for exercise for the sample. For example, given an average P_{max} of 15% and an average percent likelihood of purchase at P_{max} of 50%, we may predict an average of 7.5% of leisure time traded for exercise.

Limitations and Conclusions

This study has important limitations. First, self-report measures of physical activity (e.g., IPAQ-SF, GSLTPAQ) or exercise are poorly correlated (i.e., low to moderately) with objectively measured physical activity via accelerometers (Prince et al., 2008). Additionally, self-reported leisure time may be poorly correlated with objectively measured behavior. However, despite the known issues with self-reported physical activity, we used validated measures of behavior or attitudes towards physical activity (e.g., PACES-S, IPAQ-SF, GSLTPAQ). Second, due to the exploratory nature of the study, we did not control for multiple comparisons in the correlation analyses. Finally, while at least 28% of participants were minorities, the majority were White and non-Hispanic; results may not generalize to more diverse populations. However, the use of a convenience sample via Prolific is justified for initial task development.

In conclusion, the novel LT-EPT generates moderate rates of systematic demand data that can be fit using the exponentiated model of demand; however, instructions describing the task may be more complex than optimal. The LT-EPT demand indices are correlated with variables hypothesized to be related to exercise valuation. Importantly, all demand indices generated by the LT-EPT were related to the exercise to leisure time ratio variable, demonstrating criterion validity. The LT-EPT is a novel and potentially effective approach to quantifying exercise demand, representing an improvement in operant behavioral economic approaches to measuring exercise valuation. Future research should consider further validating the task using objective measures of exercise, physical activity, and leisure time via accelerometry data, as well as simplifying task instructions to increase rates of systematic data and task comprehension.

Tables and Figures

Table 1

Participant demographics

Characteristic	Median (*IQR*); *n* / *N* (%)
BMI	25.79 (21.85 - 29.25)
Age	33.00 (26.00 - 43.00)
Weekly Leisure Time (hrs)	40.00 (27.50 - 55.00)
Gender	
Female	87 / 175 (50%)
Male	84 / 175 (48%)
Other	4 / 175 (2.3%)
Race	
American Indian or Alaskan Native	6 / 175 (3.4%)
Asian	22 / 175 (13%)
Black	16 / 175 (9.1%)
Native Hawaiian or Other Pacific Islander	0 / 175 (0%)
Other	4 / 175 (2.3%)
Refuse to answer	4 / 175 (2.3%)
White	123 / 175 (70%)
Ethnicity	
No, not Hispanic or Latino	156 / 175 (89%)
Refuse to Answer	3 / 175 (1.7%)
Yes, Hispanic or Latino	16 / 175 (9.1%)
Education	
Less than high school	3 / 175 (1.7%)
High School diploma or equivalency (GED)	56 / 175 (32%)
Associate degree (junior college)	20 / 175 (11%)
Bachelor's degree	69 / 175 (39%)
Master's degree	16 / 175 (9.1%)
Doctorate	6 / 175 (3.4%)
Professional (MD, JD, DDS, etc.)	3 / 175 (1.7%)
Refuse to answer	0 / 175 (0%)
Other	2 / 175 (1.1%)
Income	
Less than $29,999	46 / 175 (26%)
$30,000 through $69,999	56 / 175 (32%)
$70,000 through $109,999	35 / 175 (20%)
$110,000 through $179,999	22 / 175 (13%)
$180,000 and greater	10 / 175 (5.7%)
Refuse to answer	6 / 175 (3.4%)

Demographic information of participants randomized to the LT-EPT condition.

Table 2

Summary statistics of LT-EPT demand indices

Summary Statistic	BP_1	P_{max}	$Q_{1\%}$	α
1. *M*	39	22.68	83.64	0.0007963934
2. *SD*	31.95	26.11	27.62	0.002811099
3. *Mdn*	25	12.5	100	0.0002013312
4. *IQR*	47.5	17.50	20	0.0003558776
5. *n*	136	136	136	133

Summary statistics of demand indices, excluding participants who generated nonsystematic data, failed the comprehension check, or indicated 100% probability of trading leisure time for exercise time across all prices. Participants who indicated 0% probability of trading leisure time for exercise time across all prices are included in BP_1, P_{max}, and $Q_{1\%}$ summary statistics, but not α. *M* = mean; *SD* = standard deviation; *Mdn* = median; *IQR* = interquartile range; *n* = subsample size.

Table 3

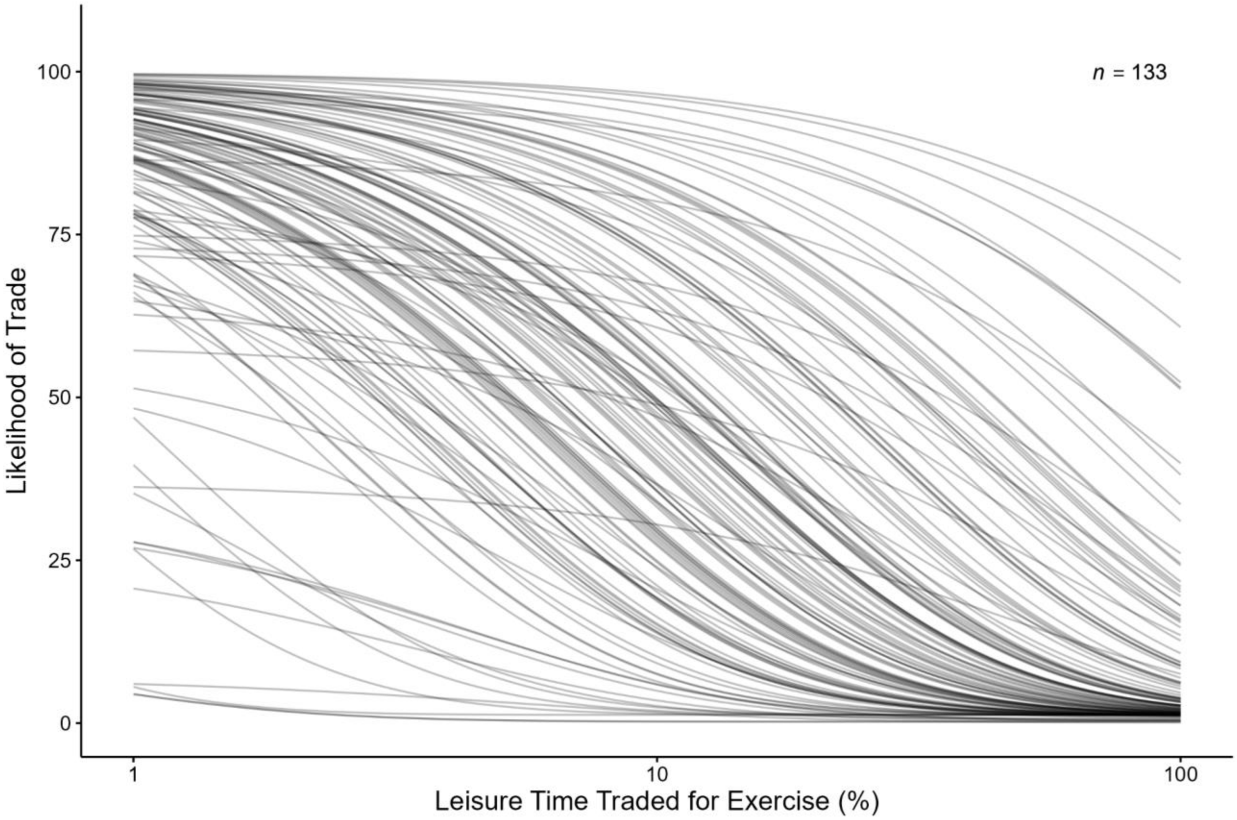
Correlations between LT-EPT demand indices and measures hypothesized to be related to exercise valuation

Variable	BP_1	P_{max}	$Q_{1\%}$	α
1. BMI	-.18* [-.34, -.01]	-.18* [-.34, -.02]	-.02 [-.19, .15]	.30** [.13, .44]
2. Age	-.21* [-.37, -.04]	-.18* [-.33, -.01]	.18* [.02, .34]	.04 [-.13, .21]
3. Exercise to leisure time ratio	.31** [.15, .45]	.35** [.19, .49]	.32** [.06, .46]	-.39** [-.52, -.23]
4. Physical activity to leisure time ratio	.36** [.21, .50]	.34** [.19, .48]	.11 [-.06, .27]	-.31** [-.46, -.15]
5. PACES-S	.35** [.19, .49]	.34** [.18, .48]	.29** [.13, .44]	-.36** [-.50, -.20]
6. GSLTPAQ	.33** [.18, .48]	.30** [.13, .44]	.19* [.03, .35]	-.38** [-.52, -.22]
7. MET	.31** [.15, .45]	.25** [.09, .40]	.11 [-.06, .26]	-.26** [-.41, -.10]

Sample size for each Spearman rank-order correlation varied from 132 to 136 pairs; see data analysis subsection for details regarding the sample size of each correlation. Values in square brackets indicate the 95% confidence interval for each correlation. * indicates $p < .05$. ** indicates $p < .01$.

Figure 1

Individual LT-EPT demand curves fit using the exponentiated model of demand



Individual models were generated for individuals who passed the task comprehension check and provided systematic data (excluding individuals who provided zero probability of consumption across all prices, for whom curves cannot be generated).

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MANUSCRIPT TWO

The effect of episodic future thinking on delay discounting and behavioral economic demand for exercise

Abstract

Physical inactivity is a major risk factor for negative health outcomes; behavioral economic demand for exercise may be a valid target to identify interventions that may increase physical activity. Episodic future thinking (EFT), the vivid imagining of personal future events, has been demonstrated to reduce delay discounting; however, little research has examined the effect of EFT on demand for exercise. In this single-session online experiment, 127 American adults not meeting physical activity guidelines were randomly assigned to generate EFT or health information thinking (HIT) control cues; participants then completed a delay discounting task or the leisure-time-as-price hypothetical exercise purchase task (in random order) while instructed to vividly imagine their EFT or HIT cues. Results indicated that EFT participants demonstrated lower delay discounting than HIT participants, while no differences were observed in demand for exercise. This research replicates previous work demonstrating that EFT lowers delay discounting, while providing early evidence that EFT may not affect demand for exercise in this population.

Keywords: episodic future thinking, exercise, purchase task, delay discounting, physical inactivity

Introduction

As of 2018, over 75% of American adults are not meeting aerobic and muscle-strengthening physical activity guidelines (Hyde et al., 2021). Inadequate physical activity has numerous negative health consequences, including increased risk of non-communicable diseases (e.g., type 2 diabetes, cardiovascular disease, and certain cancers; Katzmarzyk et al., 2022). While many factors influence the prevalence of physical activity, one potentially important (and understudied) contributor is an individual's assessment of the reinforcing value of physical activity or exercise (Flack et al., 2017a). Although the reinforcing value of a commodity or behavior is context-dependent, an individual's subjective reinforcing value of exercise is predictive of physical activity engagement (Epstein et al., 1999; Flack et al., 2017b; Roemmich et al., 2008). Thus, operant behavioral economic demand for exercise may provide a valid target for brief online or in-lab studies seeking to develop interventions to increase physical activity. Researchers could use basic, low-burden experiments to test if certain interventions may be effective to increase exercise demand, without the need to measure habitual physical activity over extended periods of time.

We have recently developed a novel hypothetical purchase task, the leisure-time-as-price exercise purchase task (LT-EPT; Brown et al., under review), to quantify the reinforcing value of exercise within an operant behavioral economic demand framework (Hursh & Silberberg, 2008; Johnson & Bickel, 2006; Roma et al., 2016). In the LT-EPT, individuals indicate their likelihood of trading leisure time for an equivalent amount of exercise time. The LT-EPT demonstrated construct validity, generating demand indices that were correlated with measures related to self-reported physical activity via the Godin-Shepard leisure time physical activity questionnaire (α: ρ = -.38, $Q_{1\%}$: ρ = .19) and physical activity enjoyment via the physical activity enjoyment scale

(α: ρ = -.36, $Q_{1\%}$: ρ = .29), suggesting that the task captures operant behavioral economic demand for exercise (Chen et al., 2021; Godin, 2011). However, to further establish the utility of demand for exercise, research must demonstrate that changes in demand for exercise correspond with changes in physical activity behaviors (and vice-versa). If such correspondence were observed, the process of developing interventions to increase physical activity and exercise behaviors may be simplified. Importantly, before researchers should examine the correspondence between change in demand for exercise and change in actual physical activity behaviors, a feasible intervention to change demand for exercise must be identified.

Episodic future thinking (EFT), the vivid imagining of possible, personal future events, has been demonstrated to reduce delay discounting (i.e., delayed reward sensitivity; Peters & Büchel, 2010; Rösch et al., 2021; Rung & Madden, 2018) and demand for certain potentially harmful reinforcers. Brief engagement in EFT has also been shown to decrease self-administration of cigarettes and hypothetical cigarette demand in adults who smoke cigarettes (Chiou & Wu, 2017; Stein et al., 2016, 2018), and hypothetical alcohol demand in individuals with alcohol use disorder (Bulley & Gullo, 2017; Collado & Stokes, 2023; Patel & Amlung, n.d.; Snider et al., 2016). Additionally, brief engagement in EFT in the laboratory has been shown to reduce caloric consumption of highly palatable foods during an ad-libitum eating task in adults and children with overweight/obesity (Daniel et al., 2013, 2015) and in young adults, where the effect of EFT on decreased consumption of chocolate confections was moderated by higher BMI values (Chang et al., 2020), and the purchase of high calorie and low nutrient foods in an online grocery shopping task (Hollis-Hansen et al., 2019). In naturalistic settings, repeated delivery of EFT has been used to reduce total calorie consumption and calories from fat in women with overweight/obesity in a food court (O'Neill et al., 2016) and has been demonstrated to reduce calories, grams of fat, and milligrams of sodium purchased by mothers with overweight/obesity who engage in grocery shopping for their household (Hollis-Hansen et al., 2020). Additionally, regular engagement in EFT may improve health behavior not related to dietary intake, including medication adherence in adults with type 2 diabetes or prediabetes (Epstein, Jimenez-Knight, et al., 2022) and alcohol consumption in adults with a desire to reduce their drinking (Athamneh et al., 2021).

While the effects of EFT on delay discounting and related health behaviors appear promising, it is unclear how EFT affects physical activity or demand for exercise. Presently, only one clinical trial has examined the effects of repeated engagement in EFT on physical activity. Specifically, in a 24-month, multi-component clinical trial in people with prediabetes, Epstein, Paluch, et al. (2022) reported that both groups (EFT and control) showed significant weight loss, improvements in glycemic control, and increases in physical activity; however, they observed no significant effect of EFT on any of these measures. This study was not powered to detect a significant effect of EFT on changes in physical activity (secondary outcome), highlighting the need for more basic research to elucidate the conditions (if any) in which EFT may promote increased physical activity or exercise demand. Given the complexity of the Epstein, Paluch, et al. (2022) clinical trial, a simpler design delivering acute (i.e., single exposure) EFT, without additional behavioral intervention components encouraging physical activity, would provide a more direct examination of the effects of EFT on exercise demand.

To this end, we conducted an online experiment to examine the effect of acute (i.e., single-session exposure) EFT on demand for exercise and delay discounting in American adults not currently meeting physical activity guidelines (Piercy et al., 2018). Participants were randomly assigned to generate EFT or health information thinking (HIT; a health information control condition, Brown et al., 2023; Rung & Epstein, 2020) cues before completing the LT-EPT and delay discounting tasks in randomized order. We chose HIT as the control condition as it has been developed for use in clinical research settings (i.e., HIT cue generation and engagement schedules can be matched with the EFT condition while controlling for participants' expectation of improvement), but has not been demonstrated to reduce delay discounting. Participants were instructed to vividly imagine or consider their cues during both tasks. We hypothesized that participants engaging in EFT would demonstrate higher demand for exercise and lower delay discounting compared to participants engaging in HIT.

Methods

Participants

Participants (*n* = 127) were recruited and completed the study on April 14, 2023, using Prolific (prolific.co), an online research recruitment platform (Peer et al., 2022). Participants were required to be residing in the US, fluent in English, and over 18 years of age. Prolific allows researchers to target participants who have provided specific answers to questions on the Prolific prescreen (a demographics survey that survey takers may update regularly); we targeted participants with answers to the following question: "How often do you engage in physical exercise per week?" Only participants who answered "Never (0 - 60 minutes per week)", the lowest option available on the Prolific prescreen, were eligible to be invited to participate. At the beginning of the recruitment period, a total of 7,351 participants met the criteria and had completed a survey on Prolific in the last 90 days and were thus eligible for recruitment. A total of 265 individuals accepted the study and began participating. Upon beginning the survey, one participant did not agree to the consent information questionnaire. A further 112 participants failed to validate their answers provided on the Prolific prescreen (i.e., did not provide the same answers in our survey as they provided in the Prolific prescreen) and were excluded. A further 3 stopped responding before randomization; of the remaining 149 participants, 75 participants were randomized to the EFT group, while 74 participants were randomized to the HIT group. Of the 75 EFT participants, 13 did not complete the experiment; of the 74 HIT participants, 9 did not complete the experiment. Participant demographics for completers (EFT n = 62; HIT n = 65) are presented in table 1.

We conducted a power analysis based on an independent samples *t*-test. Assuming a medium effect size (*d*) of 0.5 and a power of 80%, 128 participants (64 per condition) were required to detect a significant difference at the 0.05 α level using a two-tailed test. A meta-analysis on the effect of EFT on eating behaviors (Yang et al., 2019) observed a large effect size; thus, a medium effect size was chosen as a conservative estimate, as this will be the first study to examine the effect of EFT on demand for exercise.

Procedure

The experiment was conducted using Qualtrics survey software. Participants provided informed consent by reading an IRB-approved consent information sheet and indicating their agreement; acquiring written informed consent was waived by the IRB. We then validated the fluent languages and physical exercise questions from participants' Prolific prescreen. First, participants selected all languages in which they were fluent from a list of 86 common languages; participants had to select English in order to continue. Additionally, participants were asked: "How often do you engage in physical exercise per week?" with four possible responses: 1) Never (0 - 60 minutes per week), 2) Sometimes (60 - 150 minutes per week), 3) Often (more than 150 minutes per week), and 4) Rather not say. Eligible participants (based on the criteria above), then completed a demographic questionnaire, including height and weight, followed by the Exercise Valuation Assessment Scale (EVAS, a Likert scale questionnaire assessing exercise valuation; Brown et al., under review), questions about commercial gym or health center usage behaviors, and the International Physical Activity Questionnaire - Short Form (IPAQ-SF). Participants were then randomized to generate EFT or HIT cues. Afterwards, participants completed an adjusting-amount delay discounting task (Du et al., 2002) and the LT-EPT, in counterbalanced order, while reading and imaging their EFT or HIT cues. Participants self-reported weekly leisure time before completing the LT-EPT. Participants were compensated $7.80; median completion time was 42 mins, yielding an hourly compensation rate of $11.06. The full survey can be found in the supplementary materials.

Demographics and Other Participant Characteristics

Demographic questions included self-reported height and weight, education, income, gender, age, race, and ethnicity. Additionally, we asked questions about behavior related to typical exercise habits and exercise environments (Brown et al., 2021). Specifically, participants reported how many minutes they spend exercising at a gym, fitness center, or health center in a typical week. Relatedly, participants reported how many minutes they spend exercising outside of a gym, fitness center, or health center in a typical week. Participants who reported currently having a gym or fitness center membership indicated their monthly membership price in USD; participants who reported not currently having a membership were assigned values of zero. Participants completed a battery of measures (not relevant to analyses reported here) related to self-reported physical activity and perceptions of exercise, including a contemplation ladder and the IPAQ-SF (see survey file in supplementary materials for comprehensive list; Biener & Abrams, 1991; Lee et al., 2011).

EFT Cue Generation

Participants generated seven EFT cues using a self-guided cue generation survey containing detailed instructions and examples of good and bad cues (Brown & Stein, 2022). Participants first generated seven "I am" statements at each of the time frames describing a positive and personally meaningful future event (e.g., "In one month, I am at the coffee shop with my wife"), followed by rating each statement for enjoyment, importance, excitement, and vividness. Participants repeated this process across seven future time periods: one month, three months, six months, one year, three years, five years, and ten years. Participants then provided more details for each event, such as who they will be with, what they will be doing, and how they will be feeling (e.g., "In one month, I am at Sweet Donkey Coffee on a Saturday morning with my wife Liz and my dog Winston. We are enjoying our coffee on the porch and talking about what we'd like to do over the weekend. I am happy to be outside with my favorite person and animal").

HIT Cue Generation

Participants generated seven HIT cues using a self-guided cue generation survey designed to emulate the EFT cue generation survey (Brown et al., 2023; Rung & Epstein, 2020). Participants first read informational vignettes regarding different health behaviors relevant to weight control, physical activity, and glycemic control (i.e., aerobic physical activity; ultra-processed foods; self-monitoring of body weight, eating, and exercise; glycemic index; energy density; variety of foods; and strengthening exercises). After reading each vignette, participants described in one sentence something they learned from the information and rated the information on several characteristics, including: how much they liked learning the information, how important it was to learn the information, how exciting it was to learn the information, and how useful it was to learn the information. Finally, participants provided more details to their one sentence summary, including how the information fit into their existing knowledge, what the information made them think about, for whom or for what the information might be useful, and how the information made them feel.

Weekly Leisure Time

Participants self-reported the total amount of leisure time they have on a typical weekday and weekend. We defined leisure time as time spent engaging in recreational exercise, relaxing, watching television, socializing, spending time with family or friends, or engaging in hobbies. We instructed participants not to include time spent sleeping, working, in school, performing household chores, cooking meals, or commuting. We specified that recreational exercise would only include exercise performed for the sake of exercise, and not exercise that occurs while commuting or for transportation.

EFT- or HIT-cued Leisure-time-as-cost Exercise Purchase Task (LT-EPT)

In the LT-EPT, participants indicated their likelihood of giving up a percentage of their typical weekly leisure time in order to allocate that time to weekly exercise. The task instructions were designed to control for preferences in types of exercise (i.e., participants could engage in any form of exercise they desire during their purchased exercise time) and to create a closed economy (i.e., participants had no other access to exercise time except by purchasing it via leisure time). Additionally, we specified that the hypothetical exercise time could be performed throughout the week (see supplementary materials for more detail). Participants indicated likelihood across a range of 14 ascending percentages of weekly leisure time (i.e., 1%, 5%, 7.5%, 10%, 12.5%, 15%, 17.5%, 20%, 25%, 30%, 40%, 50%, 75%, 100%) while instructed to read aloud and imagine their EFT cues or read aloud and consider their HIT cues. Participants viewed each of their seven EFT or HIT cues twice across the 14 prices, in ascending or descending order of cue presentation (cue presentation order was randomly assigned). For example, in the ascending order condition, EFT participants viewed their 1-month cue during the first and second prices, then viewed their 3-month cue during the third and fourth prices, and so on. HIT participants viewed the HIT cue generated first in the cue generation task during the first and second prices, then viewed the HIT cues generated second in the cue generation task during the third and fourth prices. In the descending order condition, EFT and HIT participants viewed their cues in the reverse order. While we have no reason to believe that the order of presentation for EFT or HIT cues during the LT-EPT may affect demand for exercise, we randomized cue presentation order to limit the impact of a potential order effect.

Likelihood was reported using a sliding scale from 0 - 100, with 5-unit increments. Each price was presented on a separate page of the survey, with no option to regress within the survey. We used participants' self-reported leisure time responses to calculate the amount of leisure time to be traded at each price. We displayed this information as hours and minutes of leisure time to trade each week and each day (rounded to the nearest minute). For example, a participant reporting 2100 minutes of leisure time per week (300 minutes per day) and randomized to the EFT condition and ascending cue presentation order would have been asked the following at the 1% price: "What is the likelihood that you would be willing to give up 1% [0 hours and 21 minutes] of your weekly leisure time to engage in the same amount of weekly recreational exercise? On average, this would be 0 hours and 3 minutes per day. As you make your choices, please read aloud and imagine… [1 month EFT cue]".

All participants answered a comprehension check question following the instructions but presented on the same page in the survey. The comprehension question stated, "Thanks for reading the instructions above. What will the following questions ask you to do?". Five answer choices were presented in random order: 1) "I will indicate the likelihood of giving up a *certain* amount of weekly *leisure time* for *half* as much weekly *exercise time*", 2) "I will indicate the likelihood of giving up *one day's* with of *leisure time* for *as much* weekly *exercise time*", 3) "I will indicate the likelihood of giving up a *certain* amount of weekly *exercise time* for as much weekly *leisure time*", 4) "I will indicate the likelihood of giving up a *certain* amount of weekly *leisure time* for *as much* weekly *sleeping time*", and 5) "I will indicate the likelihood of giving up a *certain* amount of weekly *leisure time* for *as much* weekly *exercise time*". Participants passed the comprehension check by selecting answer choice 5.

EFT- or HIT-cued Delay Discounting Task

In the EFT- or HIT-cued adjusting-amount delay discounting tasks, participants made choices between smaller amounts of hypothetical money received immediately and a larger amount of hypothetical money ($1000) received after a delay while instructed to engage in EFT or HIT (Du et al., 2002; Epstein et al., 2022; Rung & Epstein, 2020). The adjusting-amount procedure occurred for six trials in each block, and was repeated across seven delays (i.e., one month, three months, six months, one year, three years, five years, and ten years) to generate an indifference point at each delay. Before beginning each block, participants were instructed to "read aloud and imagine" one complete EFT cue or to "read aloud and consider" one complete HIT cue. During each trial within a block, participants were presented with short versions of their cues (i.e., the initial, single-sentence description generated during each cue generation task task). Specifically, EFT participants were asked, "Which of the following options would you prefer when you imagine [short 1-month cue]", while HIT participants were asked, "Which of the following options would you prefer when you consider [short HIT cue 1]". Presentation of EFT cues were matched with the delay presented in each block (i.e., participants imagined their

1-month EFT cue during the 1-month delay), while HIT cues were matched with delays according to the order in which they were generated (i.e., participants imagined the HIT cue generated first during the 1-month delay). Delays were presented in randomized order.

Before completing the EFT or HIT cued delay discounting task, participants were instructed to choose between receiving different amounts of money at different points in time. Additionally, participants were instructed that choices were hypothetical, but that they should choose their answers as if they were real. All participants answered a comprehension check question following the instructions but presented on the same page. The comprehension check stated, “To confirm that you understand what you are asked to do, please select the statement that best describes the instructions". Four answer choices were presented in random order: 1) “You are asked to choose between different amounts of money as if they were hypothetical”, 2) “You are asked to choose between different amounts of money given different probabilities”, 3) You are asked to choose between different amounts of money at different points in time”, and 4) “You are asked to choose between different amounts of money disregarding your preference”. Participants passed the comprehension check by selecting answer choice 3 (Yeh et al., 2023). Additionally, participants completed four attention check questions, each presented at the end of a block. In each attention check question, participants were shown their shortened EFT or HIT cue (consistent with the previous trials in each block) while choosing between $500 now and $1000 now. Participants were considered to have correctly responded to the attention check by selecting $1000 now.

Data Analysis

All analyses were performed in R (version 4.2.1) using RStudio (Posit team, 2023). We used an α value of .05 for null-hypothesis significance testing. Data wrangling, shaping, cleaning, and visualizations were performed using the *tidyverse* collection of packages (Wickham et al., 2019). Table 1 was generated using the *gtsummary* package (Sjoberg et al., 2021). Demand indices were obtained using the *beezdemand* package; to improve skew, we log transformed alpha values before second stage analyses (Kaplan et al., 2019). Ordinal AUC values were obtained using the *discAUC* package (Friedel, 2021).

Two-stage demand analyses

Using the two-stage demand analyses approach (Kaplan et al., 2021), each individual participant's exercise demand data was fit to the exponentiated model of demand using a single nonlinear regression to estimate α (alpha; rate of change of elasticity) and Q_0 (intensity of demand; consumption at zero or near-zero price) parameters. We constrained the Q_0 parameters to a maximum of 100, reflecting the maximum possible percent likelihood of consumption. We used observed $Q_{1\%}$ (i.e., the likelihood of trading 1% of leisure time for exercise time) in the second stage of analyses, as interpretations of model-estimated Q_0 are poorly defined in time-as-price probability purchase tasks (i.e., model-estimated Q_0 represents the probability of trading 0% of leisure time for 0% of exercise time). We observed measures of breakpoint (BP_1), the last price at which participants indicated any likelihood of purchase or trade, and P_{max}, the price at which maximum expenditure occurred. A k value of 1.754661 was used for all participants, regardless of group assignment; these values were obtained by subtracting the log10 of mean consumption at the lowest price from the log10 of mean consumption at the highest price, then adding 0.5. We identified a total of 37 individuals (n = 19 EFT; n = 18 HIT) who were flagged as providing nonsystematic consumption data (n = 12 EFT; n = 12 HIT), did not pass the LT-EPT comprehension check (n = 10 EFT; n = 7 HIT), or both (n = 3 EFT; n = 1 HIT). Participants that indicated zero consumption across all prices (i.e., no demand at any price) were included in analyses and considered systematic (*n* = 11 EFT; *n* = 5 HIT); however, as this pattern of responding is unable to be fit using nonlinear regression, we assigned these individuals values of zero for all indices except α, for which we did not assign any value.

We used two ANCOVA models to test for differences between estimates of $Q_{1\%}$ and log-transformed α by group, including all responses regardless of systematicity or comprehension check results (*n* = 2 EFT participants generated negative α values that could not be log transformed and were not included in second stage α analyses). Each model specified their respective demand index as the dependent variable with group assignment as the independent variable, controlling for completion order of the LT-EPT and delay discounting tasks (i.e., LT-EPT first vs. delay discounting task first) and cue presentation order during the LT-EPT (ascending cue presentation vs. descending cue presentation). Additionally, we performed a sensitivity analysis only including demand estimates for individuals who provided systematic demand data and correctly answered the LT-EPT comprehension check question.

Delay discounting analyses

Participants' degree of delay discounting was quantified using ordinal AUC, calculated using indifference points generated from EFT- and HIT-cued delay discounting tasks (Borges et al., 2016). We used ANCOVA to test for differences in ordinal AUC between groups while controlling for completion order of the LT-EPT and delay discounting tasks (i.e., LT-EPT first vs. delay discounting task first), including all participants' ordinal AUC values. We scored the attention checks by assigning a value of 0.25 for each correctly answered attention check question; values ranged from 0 (none answered correctly) to 1 (four attention checks answered correctly). We then performed a sensitivity analysis including only ordinal AUC values for individuals who passed at least 3 of 4 attention checks (i.e., scores ≥ 0.75) and correctly answered the delay discounting comprehension check question.

Nonsystematic demand data and comprehension check comparisons

Fisher's exact tests were used to determine if rates of nonsystematic demand data generated from EFT participants differed from HIT participants (Stein et al., 2015). Next, we tested if the rates of correctly answering the LT-EPT comprehension check and the cued delay discounting tasks differed between groups using Fisher's exact tests. Additionally, we tested if rates of generating null demand data (i.e., flat zero consumption across all prices) differed between groups using Fisher's exact tests. Finally, we tested if the rates of correctly answering the attention checks embedded in the delay discounting tasks differed between groups using a Wilcoxon Rank Sum test.

Results

Demand indices

Individual fits to the exponentiated model of demand (by group assignment) are depicted in Figure 1. When including all demand data, we obtained median R^2 values of .843 and .891 for EFT and HIT groups, respectively; when including only demand data of individuals who provided systematic demand data and who correctly answered the comprehension check questions, we obtained median R^2 values of .849 and .921 for EFT and HIT groups, respectively. Summary statistics (i.e., mean, standard deviation, median, and interquartile range) for demand indices ($Q_{1\%}$, α, BP_1, and P_{max}) generated by all EFT and HIT participants are displayed in Table 2.

We conducted an ANCOVA examining log α as a function of group while controlling for task completion order and cue presentation order including all participants (EFT M = -7.85, *SEM*

= 0.26; HIT *M* = -7.19, *SEM* = 0.22). The results indicated no main effect of group, $F(1, 105) = 0.847$, $p = .359$, $\eta^2 = 0.008$, no main effect of condition, $F(1, 105) = .008$, $p = .929$, $\eta^2 = .00008$, and no main effect of order, $F(1, 105) = .468$, $p = .495$, $\eta^2 = .004$. As a sensitivity analysis, we recalculated this model using only demand indices of individuals who provided systematic demand data and who correctly answered the comprehension check question (EFT *M* = -7.91, *SEM* = 0.27; HIT *M* = -7.35, *SEM* = 0.22). Consistent with the original analysis, the results indicated no main effect of group, $F(1, 74) = 2.44$, $p = .122$, $\eta^2 = .032$, no main effect of condition, $F(1, 74) = 1.35$, $p = .249$, $\eta^2 = .018$, and no main effect of order, $F(1, 74) = 3.82$, $p = .054$, $\eta^2 = .049$.

We conducted an ANCOVA examining $Q_{1\%}$ as a function of group while controlling for task completion order and cue presentation order including all participants (EFT *M* = 54.92, *SEM* = 5.14; HIT *M* = 56.85, *SEM* = 4.79). The results indicated no main effect of group, $F(1, 123) = .10$, $p = .74$, $\eta^2 =$ 0008., no main effect of condition, $F(1, 123) = 2.31$, $p = .13$, $\eta^2 = .018$, and no main effect of order, $F(1, 123) = .17$, $p = .68$, $\eta^2 = .001$. As a sensitivity analysis, we recalculated this model using only demand indices of individuals who provided systematic demand data and who correctly answered the comprehension check question (EFT *M* = 61.86, *SEM* = 6.36; HIT *M* = 63.93, *SEM* = 5.25). Consistent with the original analysis, the results indicated no main effect of group, $F(1, 86) = .02$, $p = .87$, $\eta^2 = .0003$, no main effect of condition, $F(1, 86) = 2.25$, $p = .14$, $\eta^2 = .025$, and no main effect of order, $F(1, 86) = .92$, $p = .34$, $\eta^2 = .01$.

Delay discounting

Individual and group-level mean indifference points as a function of delay are plotted in figure 2. Boxplots depicting ordinal AUC values in each group are plotted in figure 3.

We conducted an ANCOVA comparing ordinal AUC values as a function of group while controlling for order of task completion (DD first vs. LT-EPT first) including all participants (EFT M = .642, SEM = .027; HIT M = .523, SEM = .029). The results revealed a significant main effect of group, $F(1, 124) = 9.26$, $p = .003$, $\eta^2 = .069$, but not order, $F(1, 124) = 0.465$, $p = .496$, $\eta^2 = .004$. As a sensitivity analysis, we repeated this model including only participants who passed at least three of four delay discounting attention checks and the delay discounting comprehension check (EFT M = .652, SEM = .031; HIT M = .536, SEM = .032). The results were consistent with the original analysis, indicating a significant main effect of group, $F(1, 102) = 6.96$, $p = .009$, $\eta^2 = .064$, but not order, $F(1, 102) = 0.17$, $p = .683$, $\eta^2 = .001$. Taken together, these results indicate that EFT participants demonstrated lower delay discounting than HIT participants.

Nonsystematic demand, comprehension checks, and attention checks

Fisher's exact test revealed no differences between rates of generating nonsystematic demand data between EFT (n = 50 systematic; n = 12 nonsystematic; 19.4%) and HIT groups (n = 53 systematic; n = 12 nonsystematic; 18.5%), $p = 1$. No differences were observed between rates of correctly answering the LT-EPT comprehension check question between EFT (n = 52 pass; n = 10 fail; 16.1%) and HIT (n = 58 pass; n = 7 fail; 10.8%) groups, $p = .44$. Additionally, no differences were observed between rates of generating null demand between EFT (n = 11 of 62 null) and HIT (n = 5 of 65 null), $p = .11$. Finally, a Wilcoxon Rank Sum test revealed no shift in the distribution of delay discounting attention check scores between EFT (M = 0.91, $Mdn = 1$) and HIT groups (M = .88, Mdn = 1), $W = 2030$, $p = .93$.

Discussion

The present study describes the first examination of EFT on demand for exercise, contributing to the nascent literature exploring the ability of EFT to increase the likelihood of engaging in health-promoting behaviors. Participants instructed to engage in EFT exhibited lower delay discounting compared to participants instructed to engage in HIT; however, no group differences in demand for exercise ($Q_{1\%}$, α) were observed. No differences in response quality (i.e., nonsystematic demand data, comprehension checks, or attention checks) were observed between groups on either the EFT-cued or HIT-cued delay discounting tasks or LT-EPTs. There are at least four possible explanations for the null results regarding the effect of EFT on demand for exercise: 1) the instructions to evoke EFT during the LT-EPT may have been inadequate, 2) factors inherent to the decision to trade leisure time for exercise time, 3) limitations of EFT as a behavioral intervention to increase demand for exercise, and 4) both EFT and HIT may be influencing demand for exercise to a similar degree. Below, we consider each of these possibilities in turn.

Our results replicate previous findings describing the tendency of EFT to reduce delay discounting (Brown & Stein, 2022; Bulley et al., 2019; Epstein, Paluch, et al., 2022; Rösch et al., 2021; Rung & Epstein, 2020; Rung & Madden, 2018; Stein et al., 2018), suggesting that the instructions in this experiment were able to generate cues that successfully evoked EFT when read and imagined during the delay discounting task. Even so, it is possible that the instructions to evoke EFT or HIT during the cued LT-EPT were inadequate. However, we note that the methods used in this experiment were similar to those used in previous work demonstrating an effect of EFT on demand for other commodities. For example, Athamneh et al. (2020) assessed EFT-cued demand for cigarettes and fast food by presenting participants with one randomly chosen EFT cue (out of seven total cues) during each price of a cigarette purchase task and a fast food purchase task. As in the present study, participants were instructed to vividly imagine the event as they made their choice. Stein et al. (2018) employed an identical approach as Athamneh et al. (2020) when assessing an EFT-cued cigarette purchase task. Finally, Bulley and Gullo (2017) presented EFT cues randomly at each price in an alcohol purchase task, with instructions to imagine the event before making a choice. While the present study is unable to determine definitively if the instructions to evoke EFT during the LT-EPT were inadequate, we consider this possibility to be less likely than other explanations for the observed null effect due to the methodological congruence with previous experiments.

The LT-EPT is unique among hypothetical purchase tasks in that the cost or price to purchase the commodity (i.e., exercise) is leisure time, not money. In the LT-EPT, the “healthy” or future oriented choice involves limiting one’s leisure time and engaging in a potentially aversive or less-preferred activity. Thus, the framing of the LT-EPT involves an immediate loss of a valuable commodity (i.e., leisure time) in order to gain access to another commodity whose value accrues over time and is probabilistic in nature (i.e., potential future positive health outcomes resulting from consistent exercise engagement). In contrast, the “healthy” or future oriented choice in tasks assessing demand for non-health promoting commodities (e.g., alcohol, cigarettes) involves saving money by indicating lower rates of consumption (i.e., an immediate gain), and potentially benefiting from improved health outcomes resulting from reduced consumption (i.e., a delayed gain). Said differently, individuals seeking to consume less of deleterious commodities and who indicate reduced purchasing experience a *gain-gain* of both more money and improved health outcomes as a result of decreased consumption. However, for a person seeking to be more active, purchasing more exercise by spending free time could be considered a *loss-gain.*

While EFT has been demonstrated to reduce delay discounting and demand for commodities that may cause negative health consequences when abused (e.g., alcohol, cigarettes) or over consumed (e.g., fast food), little research has demonstrated an increase in demand for commodities that may contribute to positive health outcomes (e.g., fruits and vegetables). It is possible that EFT is more likely to be effective in individuals for which reduced consumption of certain commodities is considered both an immediate and long-term gain (e.g., smokers motivated to quit or reduce cigarette consumption). In other words, EFT may be more effective in reducing consumption of unhealthy commodities (representing a gain-gain) compared to increasing consumption of healthy commodities (representing a loss-gain). This explanation is weakened when considering that an individual also experiences an immediate loss of access to reinforcement when abstaining from unhealthy commodities (e.g., loss of nicotine reinforcement as a result of smoking cessation). Additionally, EFT has been demonstrated to increase the likelihood of individuals with obesity to choose "lite" versions of snacks (e.g., jello or yogurt), further weakening this hypothesis (Segovia et al., 2020). However, it is possible that EFT is able to increase the subjective value of abstaining such that the value of abstinence exceeds the negative subjective value associated with the loss of immediate reinforcement. This may be more likely when individuals make choices for health-promoting commodities that are more likely to function as substitutes for the original commodity (e.g., "lite" yogurt vs regular yogurt, diet soda vs regular soda) as opposed to choices between commodities that are less likely to function as substitutes.

Finally, it is possible that both EFT and HIT influenced demand for exercise in the same direction and with similar magnitude, preventing discernment of group differences. In this case, EFT would be demonstrated to be no more effective than HIT, limiting its utility as a clinical intervention to increase demand for exercise. Future research should compare differences in demand for exercise between EFT, HIT, and a no-cue control.

This study has some important limitations. First, we examined only the effects of acute engagement in EFT on delay discounting and demand for exercise; it is possible that repeated exposure could reveal different results. Second, we did not ask participants about contraindications for exercise; it is possible that some participants are physically unable to engage in physical exercise, and thus would be unlikely to report trading leisure time for exercise time. Third, the LT-EPT has not been validated, although other validation studies examining correspondence between hypothetical purchase tasks and real cost and reward purchase tasks have reported positive validation results (Amlung et al., 2012; MacKillop et al., 2008; Nighbor et al., 2020; Wilson et al., 2016).

In conclusion, the present study demonstrated that acute engagement in EFT leads to lower delay discounting but not higher demand for exercise compared to engagement in HIT in adults not meeting physical activity guidelines. These findings contribute to the literature examining EFT as a potential clinical intervention by replicating previous results demonstrating the effect of EFT on delay discounting. Additionally, the null results regarding the effect of EFT on demand for exercise have potential implications for EFT as a clinical intervention. Although the effect of EFT on other health behaviors appears promising, the choice to engage in increased amounts of exercise may have unique characteristics compared to the choice to reduce consumption of harmful substances; these characteristics may prevent EFT from affecting demand for exercise. Future research should seek to better understand the interplay between demand for exercise and EFT, as well as the potential for EFT to increase demand for other health promoting commodities or behaviors (e.g., fruit and vegetable consumption, preventive medical services, sunscreen use).

Tables and Figures

Table 1

Participant demographics

	Group	
Variable	**EFT**, N = 62[1]	**HIT**, N = 65[1]
Age	37.00 (28.00, 54.75)	39.00 (30.00, 54.00)
BMI	28.22 (21.74, 32.48)	29.02 (23.75, 38.59)
Weekly Leisure Time (hrs)	41.50 (26.25, 62.00)	46.00 (32.00, 64.00)
Race		
American Indian or Alaskan Native	2 / 62 (3.2%)	2 / 65 (3.1%)
Asian	9 / 62 (15%)	7 / 65 (11%)
Black	5 / 62 (8.1%)	14 / 65 (22%)
Other	2 / 62 (3.2%)	1 / 65 (1.5%)
White	44 / 62 (71%)	41 / 65 (63%)
Ethnicity		
No, not Hispanic or Latino	54 / 62 (87%)	61 / 65 (94%)
Yes, Hispanic or Latino	8 / 62 (13%)	4 / 65 (6.2%)
Gender		
Female	32 / 62 (52%)	38 / 65 (58%)
Male	27 / 62 (44%)	24 / 65 (37%)
Other	3 / 62 (4.8%)	3 / 65 (4.6%)
Income		
Less than $29,999	18 / 62 (29%)	25 / 65 (38%)
$30,000 through $69,999	23 / 62 (37%)	19 / 65 (29%)
$70,000 through $109,999	12 / 62 (19%)	17 / 65 (26%)
$110,000 through $179,999	7 / 62 (11%)	4 / 65 (6.2%)
$180,000 and greater	1 / 62 (1.6%)	0 / 65 (0%)
Refuse to answer	1 / 62 (1.6%)	0 / 65 (0%)
Education		
Associate degree (junior college)	3 / 62 (4.8%)	9 / 65 (14%)
Bachelor's degree	15 / 62 (24%)	22 / 65 (34%)
High School diploma or equivalency (GED)	30 / 62 (48%)	28 / 65 (43%)
Master's degree	11 / 62 (18%)	5 / 65 (7.7%)
None of the above (less than high school)	1 / 62 (1.6%)	0 / 65 (0%)
Other (please specify)	1 / 62 (1.6%)	1 / 65 (1.5%)
Professional (MD, JD, DDS, etc.)	1 / 62 (1.6%)	0 / 65 (0%)

[1] Median (IQR); n / N (%)

Demographic information of participants randomized to EFT and HIT conditions.

Table 2

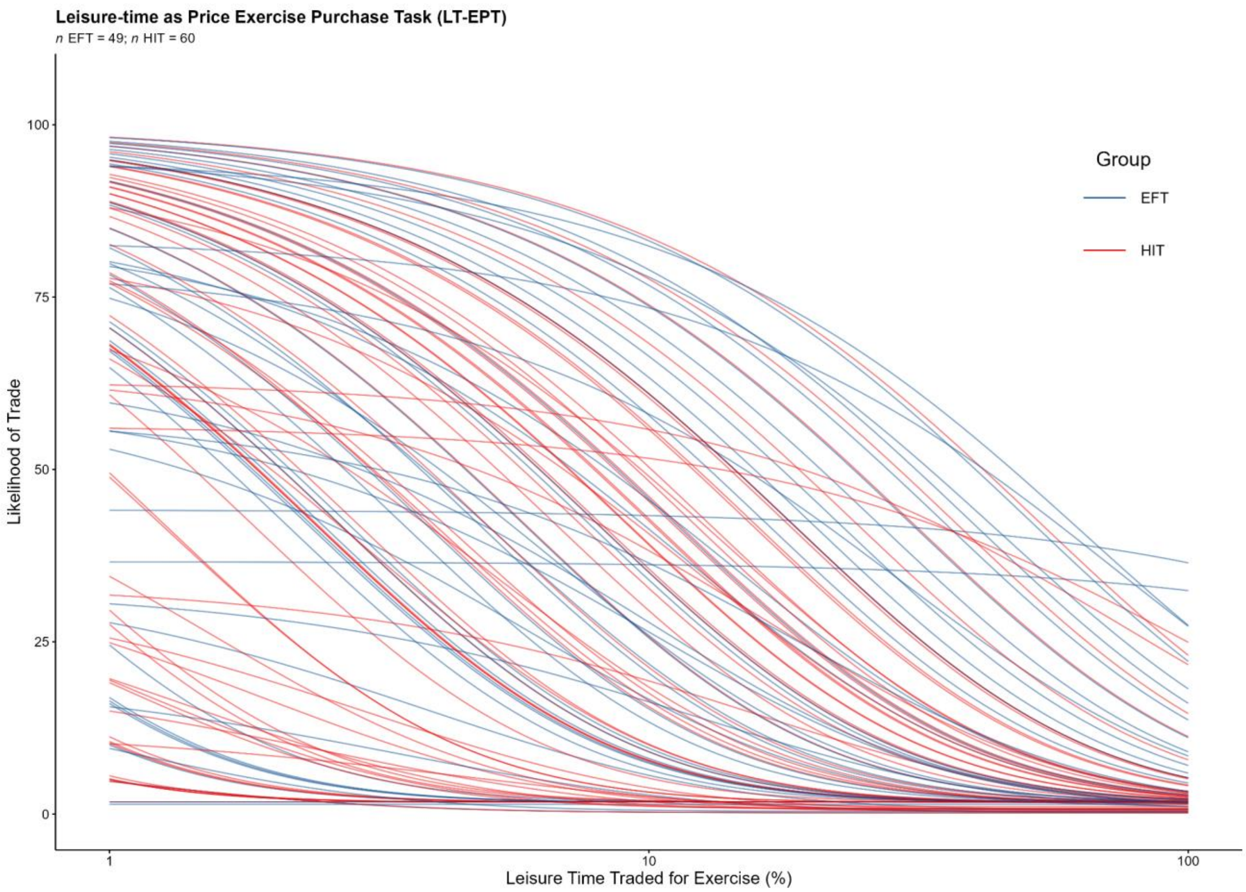
Demand indices summary statistics for EFT and HIT groups, including all participants.

Summary Statistic	BP_1		P_{max}		$Q_{1\%}$		α	
	EFT	HIT	EFT	HIT	EFT	HIT	EFT	HIT
1. Mean	38.72	31.95	26.78	20.89	54.92	56.85	0.17308111	0.03234764
2. Std. Dev.	37.61	31.99	31.95	26.97	40.46	38.61	1.0342539	0.2300453
3. Median	22.5	20	13.75	10	70	70	0.0003803754	0.0005832664
4. IQR	69.38	32.5	35	50	83.75	70	0.0009246096	0.0034334513

EFT: $n = 62$ for all indices except alpha, for which $n = 51$. HIT: $n = 65$ for all indices except alpha, for which $n = 60$.

Figure 1

Individual, cued LT-EPT demand curves by group, including all participants



n = 2 EFT participants whose demand data generated negative estimations for alpha were not included

Figure 2

Average and individual participants' indifference points as a function of ordinal delay, including all participants

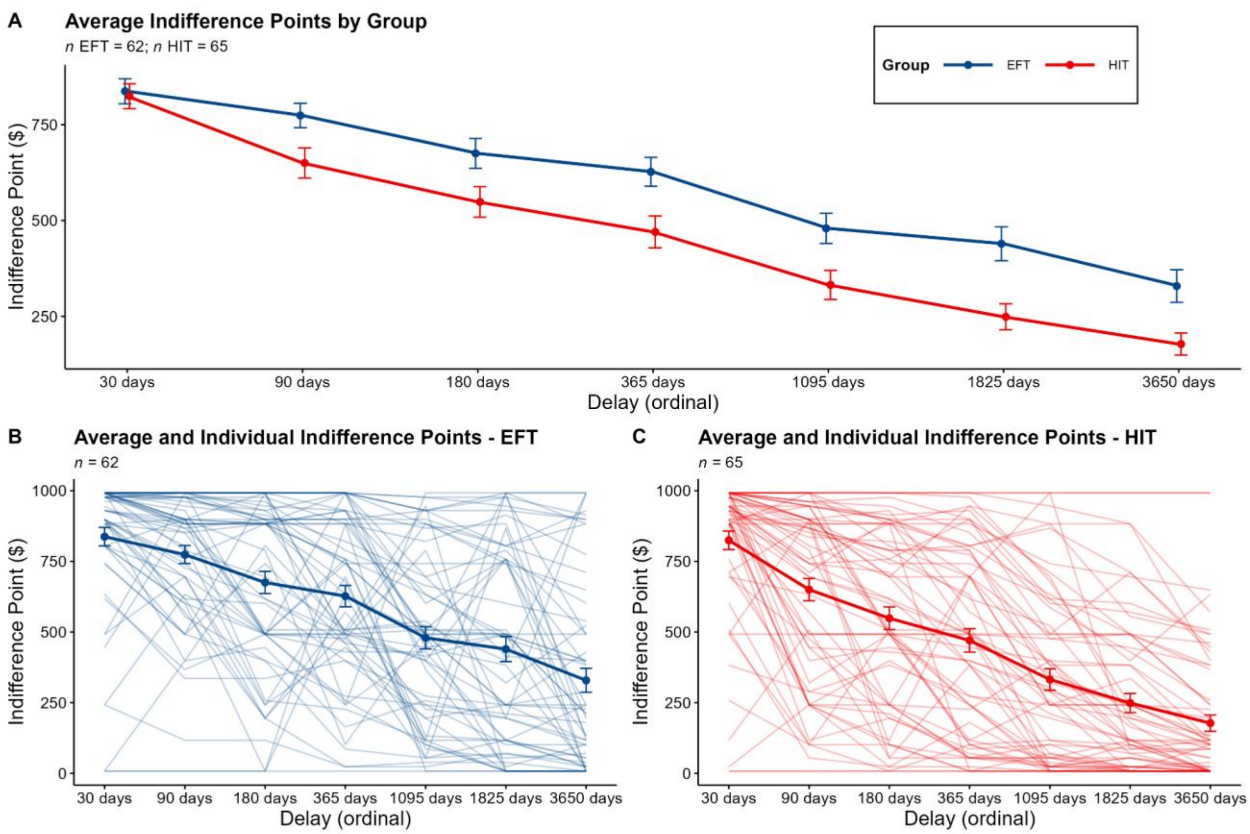
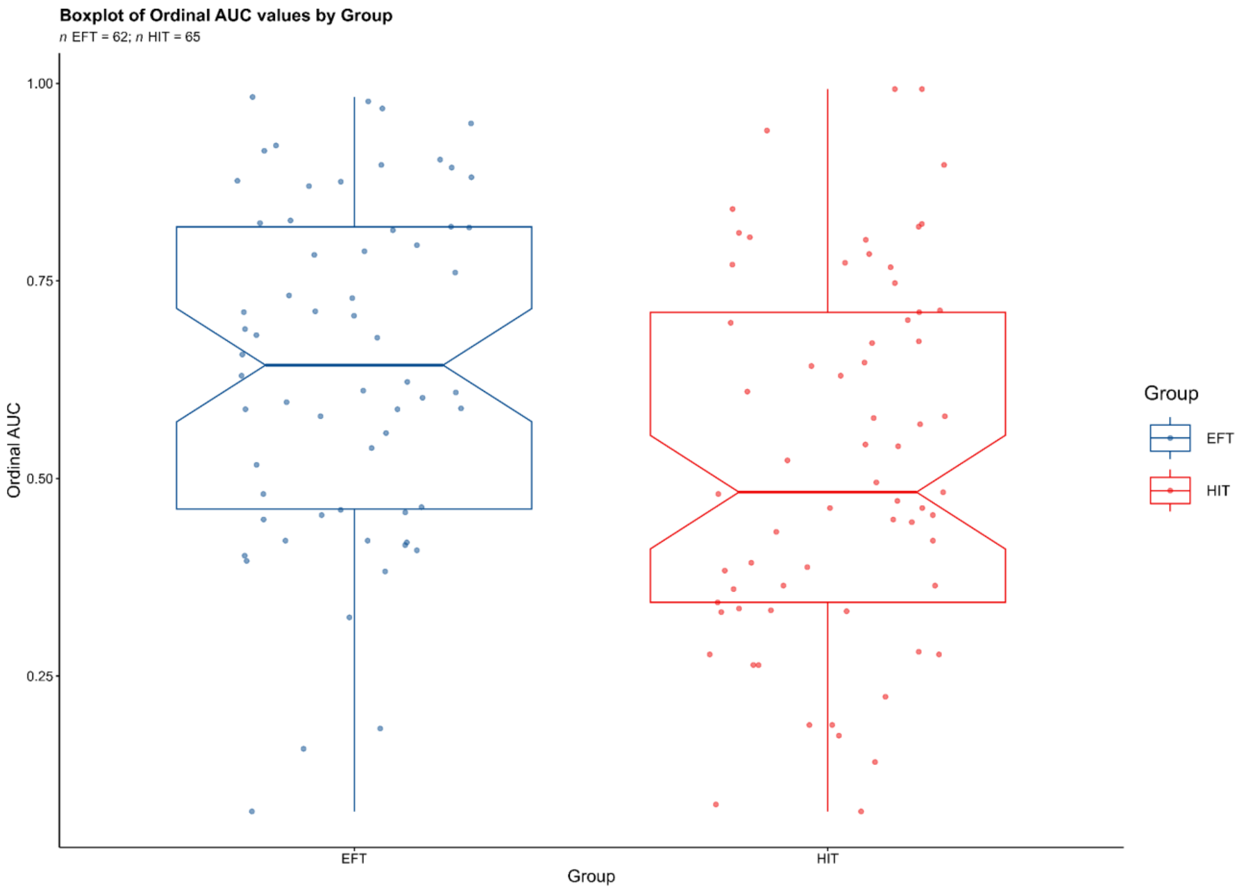


Figure 3

Notched box plots depicting ordinal AUC by group, including all participants



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MANUSCRIPT THREE

Episodic future thinking in type 2 diabetes: Effects on exercise demand, delay discounting, glycated hemoglobin, body mass index, and self-reported walking duration

Abstract

Physical activity is an important component of disease management for individuals with type 2 diabetes mellitus (T2DM), yet many individuals with T2DM are insufficiently active. The identification and development of behavioral interventions to increase physical activity in this population is warranted. Previous research has identified behavioral economic demand for exercise as a potentially valid measure of exercise valuation, which may enable more effective intervention development. While we have not observed an effect of brief (single session) engagement in episodic future thinking (EFT; vivid, personalized, prospection) on demand for exercise, it is unclear if repeated engagement in EFT is able to increase exercise demand in clinically relevant samples. Thus, we describe a preliminary analysis of a remote, 24-week RCT, examining the effect of regular engagement in EFT or a health-information thinking control (in combination with a multicomponent behavioral intervention) on glycated hemoglobin (HbA1c) and body mass index (BMI) in adults with T2DM and obesity. Additionally, we assessed exercise demand, self-reported weekly walking duration, and delay discounting. Current results (n = 71) indicate no differences between groups on any outcome measure, although reductions in HbA1c, BMI, and delay discounting were observed across sessions. These findings suggest that regular engagement in EFT may not augment the effects of effective multicomponent behavioral interventions on exercise demand or other described outcomes for adults with T2DM and obesity.

Keywords: episodic future thinking, behavioral economic demand for exercise, multicomponent behavioral intervention

Introduction

According to the Center for Disease Control's National Diabetes Statistics Report, approximately 37.3 million Americans– 11.3% of the population– have diabetes; of this number, approximately 90-95% have type 2 diabetes mellitus (T2DM; CDC, 2022, 2023). The impacts of T2DM are far-reaching, including increased patient spending on healthcare and 50% higher risk of all-cause mortality compared to adults without T2DM (Rowley et al., 2016; Seuring et al., 2015; Zimmet, 2003). Among American adults with diagnosed T2DM from 2015-2018, an estimated 34.3% were physically inactive (i.e., less than 10 mins per week of moderate or vigorous intensity activity), despite the significant benefits of physical activity for disease management in this population (e.g., improvements in blood glucose, reduced risk for cardiovascular disease; CDC, 2023; Colberg et al., 2016).

One behavioral characteristic that may be relevant for T2DM management is delay discounting, the tendency to devalue a reward as a function of the delay to receipt (Odum, 2011). Among individuals with T2DM, higher rates of delay discounting (i.e., greater preference for smaller but more immediate rewards) are associated with reduced levels of disease management behaviors and worsened disease outcomes, including higher HbA1c (Madsen et al., 2019). More broadly, higher rates are associated with poorer dietary choices, including increased likelihood of purchasing higher energy density foods or foods with lower Healthy Eating Index (2015) scores (Appelhans et al., 2012, 2019; Epstein et al., 2010). Importantly, increased rates of delay discounting are associated with decreased levels of physical activity (Daugherty & Brase, 2010;

Hunter et al., 2018; LeComte et al., 2020; Tate et al., 2015), suggesting that delay discounting may be a relevant treatment target to increase physical activity in adults with T2DM.

The ability to measure an individual's assessment of the reinforcing value of physical activity or exercise may enable the development of more effective behavioral interventions to increase physical activity or exercise (Epstein et al., 1999; Flack et al., 2017; Roemmich et al., 2008). We developed a novel hypothetical purchase task, the leisure-time-as-price exercise purchase task (LT-EPT), to better conceptualize and measure the reinforcing value of exercise via operant behavioral economic demand (see Brown et al., under review and Brown & Stein, in preparation, for more details). In Brown et al. (under review), we established construct validity for exercise demand measured using the LT-EPT by demonstrating acceptable rates of systematic data and significant, moderately strong correlations between demand indices and measures of self-reported exercise and physical activity time. In Brown and Stein (in preparation), we subsequently used the LT-EPT during a single-session, online experiment to examine the effects of brief engagement in episodic future thinking (EFT, the act of thinking vividly about personalized future events) on demand for exercise and delay discounting in adults not meeting physical activity guidelines. Participants were randomly assigned to engage in EFT while completing the LT-EPT or to engage in health information thinking (HIT), a control condition in which participants think about their impression of health-related informational vignettes (Brown et al., 2023; Rung & Epstein, 2020). While individuals randomized to the EFT condition demonstrated reduced delay discounting (i.e., increased likelihood of reporting a preference for larger, delayed rewards) compared to individuals randomized to the HIT condition, we did not observe a difference in demand for exercise between groups. Additionally, previous research examining EFT as part of a multi-component behavioral intervention to improve glycemic control in adults with prediabetes did not observe an effect of EFT on physical activity measured using accelerometers, despite observing lower rates of delay discounting in the EFT group and increased rates of physical activity across time (Epstein et al., 2022).

Although EFT may have potential as an easily delivered intervention to increase an individual's likelihood of engaging in certain health-promoting behaviors (e.g., reduced caloric consumption) and reduce delay discounting, more work is needed to better understand the conditions in which EFT may serve as a valuable clinical tool to increase exercise demand or physical activity engagement (Brown & Stein, 2022). Specifically, it is possible that the potential for EFT to increase physical activity or demand for exercise is limited to more clinically relevant populations (i.e., those in which regular activity is central to disease management) or that EFT interventions would benefit from longer durations of exposure (i.e., weeks or months). To this end, we examined the effect of EFT on demand for exercise, self-reported physical activity, and delay discounting in adults with obesity and poorly controlled T2DM in the context of a fully remote, 24-week RCT. In addition to EFT or the HIT control, all participants experienced a multicomponent behavioral intervention (adapted from materials used by Epstein et al., 2022) consisting of individualized case management, educational modules, and self-monitoring of food and physical activity; the goal of the intervention was to decrease caloric intake and control blood sugar. The primary outcome of the trial was to examine the effect of repeated engagement in EFT or a health-information control (i.e., HIT specific to T2DM management) combined with the multicomponent behavioral intervention on glycated hemoglobin (HbA1c, a biomarker measuring recent blood glucose levels) and body mass index (BMI) measured over three assessment sessions (i.e., baseline, 8 weeks, 24 weeks). Behavioral assessments measured demand for exercise, self-reported physical activity (specifically, weekly walking duration), and delay discounting. Thus, the present manuscript analyzes a subset of data from an ongoing RCT; we examine between-group comparisons within each assessment session for exercise demand, self-reported weekly walking duration, delay discounting, HbA1c, and BMI.

Methods

Participants

We recruited n = 71 adults with poorly controlled T2DM and obesity. As the sample size was tied to power analyses completed to detect an effect of EFT on the co-primary outcomes of HbA1c and BMI, we did not perform an *a priori* power analysis; however, the observed effect of repeated EFT on exercise demand may provide preliminary effect sizes for future work. We recruited potential participants from two main sources: 1) community-based participants, using paid social media advertising (e.g., Facebook, Craigslist, Nextdoor), physical fliers, and paid marketing emails, and 2) Carilion Clinic patients, using fliers and information sheets in medical waiting rooms and emails delivered to Carilion Clinic patients. Interested participants were invited to complete an online prescreen to assess eligibility. Afterwards, potentially eligible participants were contacted by research staff to schedule an informed consent session. After providing written informed consent, we measured participants' weight and HbA1c to confirm eligibility. Specifically, participants were required to have BMI >= 30 and an HbA1c >= 7.7%, measured during the informed consent session using participants' personal scale (or one provided by the lab) and an A1c Now test kit (PTS Diagnostics, Whitestown, IN), respectively. Exclusion criteria included: non-ambulatory, type 1 diabetes, intellectual impairment or unmanaged psychiatric conditions that may affect behavioral adherence, were currently pregnant or breastfeeding, recent participation in a research study involving EFT, current participation in a formal weight loss intervention, had lost 5% or more of their body weight in the six month, did not own a cell phone, were using certain medications that reduce blood glucose or cause weight loss (e.g., glutides, phentermine), or had undergone bariatric surgery. Demographic information for participants included in the present analyses is depicted in Table 1.

Procedure

All participants experienced a 24-week, fully remote, multi-component T2DM management and weight loss intervention, including: dietary and physical activity education; self-monitoring of weight, physical activity, and diet; and individualized case management with a trained member of the research team. Beginning in week 3, participants were randomized to generate EFT or HIT cues; participants were then prompted to engage with their EFT or HIT cues (i.e., vividly imagine or consider) three times per day for the remainder of the study. Assessment sessions occurred during study week 0 (baseline), week 8 (assessment 2), and week 24 (assessment 3). A detailed timeline of intervention components and assessments is presented in Figure 1. All intervention and assessment sessions involving contact with research staff occurred using HIPAA-compliant Zoom (San Jose, CA) telecommunication software.

Assessments

Assessment sessions occurred in week 0 (baseline assessment), week 8 (assessment 2), and week 24 (assessment 3). Participants completed assessment sessions while on Zoom with research staff; sessions typically lasted between 1.5-2 hours. Sessions began with biometric measurements (i.e., HbA1c and weight). Participants then completed an assessment battery via Qualtrics, including: demographic information; self-reported physical activity using the IPAQ-SF; delay discounting; and the LT-EPT.

HbA1c and weight

We obtained two measurements of HbA1c in each assessment to mitigate the impact of device measurement error in HbA1c (Gough et al., 2023); research staff recorded the measurement by asking participants to display the test kit results on their video feed. To measure weight, we provided participants with FitBit Aria scales (Fitbit, Inc., San Francisco, CA). Participants were instructed to ensure that their scale laid on a flat surface before measuring in triplicate. We verified weight measurements taken using the FitBit Aria scale by confirming values reported by participants during the session with values displayed on the FitBit dashboard associated with the account linked to their scale or using visual confirmation of the scale reading over Zoom. Due to the remote nature of the assessment, we obtained height data using self-report.

Demographics

The demographic questionnaire included common measures, such as race, ethnicity, sex, education, and family income (see Table 1).

IPAQ-SF

In the IPAQ-SF, participants self-reported their typical weekly physical activity; specifically, time spent engaging in walking, moderate-intensity, vigorous-intensity, and sedentary activities (Lee et al., 2011).

Delay discounting

The delay discounting task assessed preference between a larger, delayed reward ($1000) and a smaller, sooner reward across seven delays (i.e., 1 month, 3 months, 6 months, 1 year, 3 years, 5 years, and 10 years); the amount of the smaller reward titrated up or down following participant choices (Du et al., 2002). We embedded four attention check questions (i.e., “Which of the following options would you prefer: $500 now or $1000 now”) at the end of 1 month, 6 months, 3 years, and 10-year delay blocks; delay blocks were presented in random order (Epstein et al., 2022).

LT-EPT

The LT-EPT assessed participants' likelihood of trading weekly leisure time for an equivalent amount of weekly exercise time; the task had a price density of 18. As described in Brown et al. (2023), the LT-EPT asks participants to indicate their hypothetical likelihood to trade leisure time for an equivalent amount of exercise time. We included a comprehension check question following task instructions (see Brown et al., 2023; Brown & Stein, 2023).

Intervention

Educational modules

Participants were instructed to complete educational modules (i.e., readings and quizzes) containing basic information regarding health-promoting dietary patterns and health-behavior change strategies. Topics of the educational modules included an introduction to the program, a review of the Traffic Light Diet (Epstein, 2022; Epstein et al., 2022); self-monitoring of food, weight, and activity; episodic future thinking or healthy information thinking (the control condition); meal planning; and physical activity. Participants were instructed to read and complete at least one chapter each week for the first six weeks of participation (in the order listed above).

Nutrition Education

The primary goal of the intervention was to enable participants to achieve a modest caloric deficit sufficient to lose 1-2 lbs per week and to reduce total carbohydrate intake to approximately 40% or less of total calories. We used the Traffic Light Diet as the primary basis to conceptualize a health-promoting dietary pattern. The Traffic Light Diet categorizes food as red, yellow, or green. Generally, red foods have higher energy density relative to yellows or greens, such as full fat dairy products, cooking oils, foods high in added sugars, or fatty proteins. Yellow foods have higher energy density relative to green foods but less than red foods, such as cereals and starchy root vegetables, fruits, reduced fat dairy products, or lean proteins. Green foods are foods lower in energy density relative to yellow and red foods; only vegetables and mushrooms are categorized as greens, such as carrots, garlic, bok choy, or enoki mushrooms. Participants are encouraged to reduce consumption of red foods, moderate and employ portion control regarding yellow food consumption, and to increase consumption of green foods. For participants who began the study with existing eating plans (e.g., carbohydrate intake less than 40% of daily calories), we tailored our nutrition approach to promote reduced caloric consumption and appropriate carbohydrate consumption.

Self-monitoring of food, weight, and physical activity

Participants were provided with an online food diary (MyNetDiary.com) account and instructed to self-monitor daily food consumption and physical activity, and at least weekly body weight measurements. Participants were provided with individualized calorie and macronutrient targets. Specifically, participants were provided with daily calorie goals calculated using the Dietary Reference Intake (National Academies of Sciences, Engineering, and Medicine, 2023) equation for total energy expenditure in adults, adjusted for light physical activity and a target of 0.625 - 1.25 kg of weight loss per week (approximately 650 calories less than estimated TDEE). Macronutrient goals were set as 40% of daily calorie intake from carbs, 30% from protein, and 30% from fat. Physical activity goals were based on the Physical Activity Guidelines for Americans, which recommends that adults participate in at least 150 minutes of moderate-intensity aerobic physical activity weekly, in addition to full body muscle-strengthening activity at least twice weekly (Piercy et al., 2018).

Case management

Eleven individualized case management sessions (via Zoom) occurred throughout the study in de-escalating frequency (see Figure 1). In general, case management sessions guided participants' adherence to the intervention by providing feedback on participants' efforts to change behaviors and incorporate strategies described in the educational modules. Specifically, case managers reviewed previously established goals, troubleshot barriers that prevented reduced calorie intake, and assisted participants in setting feasible behavior-change goals each session. Case management sessions typically lasted 20-30 minutes.

To ensure treatment fidelity of case management sessions between research staff and over time, case managers met bi-weekly with supervisors. Supervisors listened to case management sessions, then provided feedback on case managers' adherence to session checklists and discussed how to apply the information in the educational modules to specific participant challenges.

Randomization

Participants were randomly assigned to EFT or HIT groups in week 3. We employed a biased coin flip procedure to allocate participants to groups while balancing groups on baseline BMI, baseline delay discounting (quantified as the mean indifference point of all delays), and rurality (binary variable coded as urban or rural; Frane, 1998; Koffarnus et al., 2021).

General cue generation and engagement

In week 3, participants generated seven EFT or HIT cues in a session guided by research staff (i.e., interview-guided; Brown & Stein, 2022). Research staff transcribed participant responses to the survey questions, while attempting to provide minimal suggestions for content or details. For the remainder of the study, participants received thrice-daily email or text prompts to access and engage with (i.e., vividly imagine or consider) their EFT or HIT cues for between 15-30 seconds, with text prompts being sent before participants' self-reported mealtimes. Throughout the course of the study, participants regenerated seven EFT or HIT cues using identical methods in weeks 8, 16, and 24; during weeks 12 and 20, participants regenerated an additional two cues (specifically, one month and three-month EFT cues for EFT participants). During case management sessions, research staff encouraged participants to regularly engage with their cues when prompted or during challenging food or activity choice scenarios. Both the EFT and HIT cue generation interview have been described and shared previously (Brown et al., 2023; Brown & Stein, 2022). We created informational vignettes relevant to T2DM management to allow for the generation of additional HIT cues throughout the study; topics included ultra-processed foods, glycemic index, medication adherence, grocery shopping, and others.

Data analysis

Outcome variable calculations

We calculated averages of duplicate HbA1c measurements and triplicate weight measurements at each assessment session, then calculated BMI using average weight at each assessment session and height self-reported at baseline. We scored the IPAQ-SF to obtain self-reported weekly walking minutes (for the previous week) at each assessment session. We chose to analyze only walking duration data due to *post-hoc* concerns regarding the quality of self-reported physical activity data generated by the IPAQ-SF (i.e., implausibly high self-reported durations of moderate and vigorous physical activity). We square-root transformed weekly walking duration values prior to analyses due to non-normal distributions. We calculated ordinal

AUC from indifference points generated by the delay discounting task at each assessment session using the R package *discAUC* (Borges et al., 2016; Friedel, 2021). We calculated the median length of engagement time with EFT or HIT cues (accessed by participants following thrice daily prompting or unprompted access), and the total number of times participants accessed cues throughout the study; we compared differences in cue engagement between groups using independent samples *t*-tests.

We fit demand data generated by the LT-EPT to the exponentiated model of demand for each individual at each assessment session using the R package *beezdemand*, obtaining estimates of α (alpha; rate of change of elasticity) and Q_0 (intensity of demand; consumption at zero or near-zero price) parameters (Kaplan et al., 2019; Koffarnus et al., 2015). We log transformed estimates of α prior to second-stage analyses due to non-normal distributions. We observed measures of $Q_{1\%}$, the participant's likelihood to trade 1% of leisure time for an equivalent amount of exercise time; breakpoint (BP_1), the last price at which participants indicated any likelihood of purchase or trade; and P_{max}, the price at which maximum expenditure occurred. A k value of 1.48625 was used for all participants, regardless of group assignment or assessment session; this value was determined by subtracting the log10 of mean consumption at the lowest price from the log10 of mean consumption at the highest price, then adding 0.5. We did not fit curves for nonsystematic demand data according to the criteria outlined by Stein et al. (2015); however, we did not consider zero responses (i.e., zero likelihood of trading leisure time for exercise time) across all prices to be nonsystematic. However, as this pattern of responding is unable to be fit using nonlinear regression, we assigned these individuals values of zero for all indices except α, which may be considered non-defined when participants indicate no consumption.

Mixed-effect model specifications

To examine the effect of group assignment, assessment session, and the interaction between group and assessment, we fit linear mixed-effects models specifying the above outcomes as dependent variables using the R package *lmerTest* (Kuznetsova et al., 2017). In all models, we specified group (dummy coded; EFT = 1, HIT = 0), session (coded as a categorical variable), and the interaction of group and session as fixed effects. To account for clustering within participants, we included a random intercept for participants to account for repeated measures within the same individuals. As mixed-effects models handle missing data well, we did not impute missing data. We used maximum likelihood estimation (MLE) to fit the model to the data. Satterthwaite's method was used to compute approximate degrees of freedom for *t*-tests associated with fixed effect coefficients; these test the null hypothesis that the corresponding fixed effect coefficient is equal to zero, implying that the predictor is not related to the dependent variable (Luke, 2017). For all models regardless of significant main effects, we performed three planned contrasts with Bonferroni adjustment using the R package *emmeans* (Lenth et al., 2023) to test for the effect of group assignment within each assessment session.

Results

Of the $n = 35$ participants who completed baseline and were assigned to the EFT group, we collected data during assessment 2 (week 8) for $n = 30$ and during assessment 3 (week 24) for $n = 18$. Of the $n = 36$ participants who completed baseline and were assigned to the HIT group, we collected data during assessment 2 (week 8) for $n = 28$ and during assessment 3 (week 24) for $n = 18$.

We observed no differences in EFT or HIT cue engagement between groups. Specifically, two independent samples *t*-tests revealed no difference in the average number of visits for each participant (i.e., cue engagements) between EFT (M = 210.5, SD = 160.3) and HIT groups (M = 277.5, SD = 167.3), $t(66.7) = -1.69$, p = .094, and no difference in the average median time (in seconds) spent engaging with cues for each participant between EFT (M = 7.7, SD = 7.8) and HIT groups (M = 6.5, SD = 6.5), $t(65.6) = 0.71$, p = .48.

In the baseline assessment, we observed 4 (11.4%) and 7 (19.4%) nonsystematic LT-EPT responses for EFT and HIT groups, respectively. In the week 8 assessment, we observed 3 (10%) and 5 (17.9%) nonsystematic responses for EFT and HIT groups, respectively. In the week 24 assessment, we observed 1 (5.6%) and 3 (15%) nonsystematic responses for EFT and HIT groups, respectively. Demand curves depicting model-estimated likelihood of trading leisure time for exercise time for EFT and HIT participants across sessions are depicted in Figure 2.

For each outcome variable, we present summary statistics via boxplots, linear mixed-effects model results via tables, planned contrasts of estimated marginal means via tables, and plots of estimated marginal means associated with the planned contrasts. Specifically, tables and figures describing α are depicted in Tables 2-3 and Figures 3-4; no main effect or interaction of group or session were significant. Tables and figures describing $Q_{1\%}$ are depicted in Tables 4-5 and Figures 5-6; no main effect or interaction of group or session were significant. Note that estimations of α (i.e., elasticity of demand) represent participants' sensitivity to increased leisure-time costs to engage in exercise; as such, lower α values (i.e., less sensitive) indicate higher demand for exercise time. Empirically observed values of $Q_{1\%}$ indicate participants' self-reported likelihood to trade 1% of leisure time for an equivalent amount of exercise time. Tables and figures describing self-reported weekly walking minutes are depicted in Tables 6-7 and Figures 7-8; no main effect or interaction of group or session were significant. Tables and figures describing ordinal AUC are depicted in Tables 8-9 and Figures 9-10; a significant effect of session (higher ordinal AUC at week 8 compared to baseline), but not group, was observed. Note that ordinal AUC represents the proportion of choices indicating preference for the larger, delayed reward during the delay discounting task; as such, higher ordinal AUC values indicate lower rates of delay discounting. Tables and figures describing HbA1c are depicted in Tables 10-11 and Figures 11-12; a significant effect of session (lower HbA1c at both week 8 and week 24 compared to baseline), but not group, was observed. Finally, tables and figures describing BMI are depicted in Tables 12-13 and Figures 13-14; a significant effect of session (lower BMI at both week 8 and week 24 compared to baseline), but not group, was observed.

Discussion

The present longitudinal RCT examined the effects of EFT combined with a behavioral intervention on measures relevant to T2DM management, including: demand for exercise, self-reported physical activity, delay discounting, HbA1c, and BMI. We observed no main effect of group (EFT vs. HIT) or session on either measure of exercise demand (α, $Q_{1\%}$) or self-reported weekly walking time, indicating that neither EFT nor the multicomponent behavioral intervention increased demand for exercise or self-reported physical activity. Main effects of session were observed in HbA1c, BMI, and delay discounting; however, no group by session interactions were observed. Taken together, these findings suggest that study participation (specifically, the multicomponent behavioral intervention received by both groups) was effective in reducing delay discounting and enabling behavior change (i.e., reduced caloric consumption or behaviors related to improve glycemic control), but did not change demand for exercise or self-reported weekly walking duration.

To better interpret the observed null effect of group on all outcome variables, we examined participants' engagement with EFT or HIT cues throughout the 21 weeks following randomization. We observed no differences in participants' average number of cue engagements between groups; similarly, we observed no differences in participants' median length of time spent engaging with cues. Participants were instructed to view EFT or HIT cues three times per day for 21 weeks, for a total of 441 views. In the EFT group, the median percent of cues viewed by participants was 73.02 (SD = 39.29); in the HIT group, the median percent of cues viewed by participants was 74.83 (SD = 36.64). These findings increase our confidence that participants were actively engaging with prompts to engage with their cues, suggesting that the observed null group effects were not caused by a lack of engagement with EFT or related to differences in cue engagement between groups.

The null effect of EFT on demand for exercise (α, $Q_{1\%}$) and self-reported weekly walking duration is consistent with Brown and Stein (in preparation), in which no effect of EFT on demand for exercise was observed in an online sample of US residents not meeting physical activity guidelines (Piercy et al., 2018). Specifically, we observed small unstandardized effects of EFT on α and $Q_{1\%}$ at each assessment session (at most, differences of 0.3 log α units and 6.4% likelihood to trade 1% of leisure time for exercise), suggesting a clinically insignificant effect. However, participants in Brown and Stein (in preparation) completed the LT-EPT while instructed to vividly imagine or consider their EFT or HIT cues; in the present study, participants were not instructed to imagine or consider cues while completing the LT-EPT. Additionally, Brown and Stein (in preparation) arranged a single-session exposure to EFT cue generation and engagement; the present study includes multiple exposures to cue generation and repeated prompts for engagement over 21 weeks. While complicated by methodological differences, these results suggest that EFT may not be effective to increase exercise demand or actual physical activity despite the clinical relevance of physical activity in adults with T2DM or the increased exposure to EFT. In Brown and Stein (in preparation), we speculate that EFT may be less likely to increase the reinforcing value of certain commodities whose consumption may have high perceived opportunity cost, as consumption of these commodities involves an immediate loss of reinforcement (e.g., replacing leisure time with exercise time incurs less time for relaxation) despite the potential for increased reinforcement in the future. In comparison, EFT may be more likely to decrease the reinforcing value of certain commodities in which abstinence may have lower perceived opportunity costs, as abstaining from these commodities involves an immediate gain (e.g., reduced consumption of fast food or cigarettes incurs monetary savings) and the potential for increased reinforcement in the future.

While abstaining from consuming preferred commodities (e.g., fast food or cigarettes) also involves an immediate loss of reinforcement, it is possible that EFT increases the subjective value of the delayed reinforcement associated with abstinence beyond the subjective value of the immediate loss for some commodities. In the case of trading leisure time for exercise time, EFT does not appear to increase the subjective value of the delayed reinforcement (i.e., improved health outcomes) beyond the subjective value of the immediate loss (i.e., reduced leisure time). For EFT to change health-behaviors, the subjective reinforcing value for both the immediate and delayed outcomes associated with the health-promoting behavior (e.g., exercise) must become greater than the subjective reinforcing value for both the immediate and delayed outcomes associated with the current behavior (e.g., sedentary behavior) following the intervention.

Further speculation can be applied to the present sample of adults with obesity and T2DM. It is possible that the behavioral intervention did not provide enough emphasis on the benefits and importance of physical activity for T2DM management; indeed, the educational modules focus on behavior change related to eating behaviors, including only one chapter (presented in week 6) focused on strategies to increase physical activity levels. Regardless of the underlying mechanism(s) which may explain the null effect of EFT on demand for exercise or self-reported weekly walking duration, these findings suggest that the contexts in which EFT may function as an effective clinical tool to improve these outcomes are limited (e.g., highly specific clinical samples, if they exist at all), casting doubt on the utility of EFT as an intervention to increase physical activity. However, we note that there are significant limitations regarding the accuracy of measurement for physical activity using self-report methods, reducing our confidence in our findings regarding the effect of group or session on physical activity (Prince et al., 2008). If future research continues to explore EFT as an intervention to increase demand for exercise or actual physical activity, objective measures of physical activity will improve inference quality. Additionally, future research should consider the potential for contraindications to exercise to mask the effects of EFT or other behavioral interventions on physical activity. While randomization reduces the likelihood of unequal distributions of contraindications between groups, it is possible that both groups were equally unlikely to increase weekly walking duration due to contraindications commonly associated with poorly controlled T2DM, such as foot or nerve problems, or commonly comorbid conditions that require careful consideration when engaging in increased levels of physical activity (e.g., heart disease, rheumatoid arthritis).

Despite previous research demonstrating that EFT consistently reduces delay discounting (e.g., Rung & Madden, 2018; Ye et al., 2021), we did not observe an effect of EFT on delay discounting. In additional to the longitudinal nature of the present study, our methods deviated from previous research which demonstrated lower delay discounting following engaging in EFT compared to HIT (Brown et al., 2023; Rung & Epstein, 2020) by assessing uncued delay discounting during assessment sessions as opposed to cued delay discounting (i.e., participants were not instructed to vividly imagine or consider their EFT or HIT cues during the delay discounting task). While one online study suggests that EFT may not reduce delay discounting if not cued during the task (Rung & Madden, 2019), a previous longitudinal RCT similar in design to the present study (although utilizing a different control condition) did observe a reduction in delay discounting in the EFT group during both uncued and cued delay discounting tasks (Epstein et al., 2022). However, Epstein et al. (2022) used a daily check-in control; as such, during cued discounting, the control group was shown a blank page before delay blocks (in contrast to instructions to read and consider HIT cues during the present study). Thus, it is possible that while HIT may not affect delay discounting in single-session experiments, repeated engagement in HIT in the context of a multicomponent behavioral intervention may have affected delay discounting in a manner consistent with the effects of EFT. Indeed, we observed a significantly lower rate of delay discounting in the second assessment session (week 8) compared to the baseline session, indicating that engagement in the multicomponent behavioral intervention may also have led to reductions in delay discounting regardless of group assignment. However, the effect of session at week 24 on delay discounting was not observed to be significantly different from delay discounting at baseline. If the multicomponent behavioral intervention was responsible for the reduction in delay discounting observed in week 8, it is possible that fading components of the intervention (i.e., reduced case management frequency, completion of education modules) are responsible for the null effect of session on delay discounting in week 24. Additionally, the null effect could represent regression to the mean (i.e., baseline levels of delay discounting).

We did not observe an effect of EFT compared to HIT on HbA1c or BMI, although we did observe an effect of session at both the second (week 8) and third (week 24) assessment sessions. These results are consistent with Epstein et al. (2022), who also found significant decreases in HbA1c and BMI across time, but not by group, in adults with prediabetes. Indeed, the multicomponent behavioral intervention employed in this study, including the Traffic Light eating plan, educational modules, and personalized case management, was modeled after the behavioral intervention utilized by Epstein et al. (2022), with at least three research staff involved with implementing the behavioral intervention in both studies. However, our intervention differed in some key ways: first, the intervention, in addition to informed consent and assessment sessions, was delivered entirely remotely, and secondly, the behavioral intervention was reduced in intensity, while EFT engagement was increased in intensity. Specifically, we scheduled less case management sessions (11 vs. 24), removed certain topics in the educational modules, eliminated interactive group education meetings, and increased the frequency of prompts to engage with EFT or HIT cues (3/day for 24 weeks in the present study vs 3/day for two weeks, 2/day for six weeks, and once per day for 15 weeks). We made these behavioral intervention changes following speculation by Epstein et al. (2022) that too intensive a behavioral intervention may create a floor effect, preventing EFT from affecting outcomes in addition to the behavioral intervention; despite deintensifying the behavioral intervention, we still did not observe an effect of EFT on HbA1c or BMI.

In conclusion, the null effects of EFT vs. HIT on all present dependent variables casts doubt on the utility of EFT as a clinical tool for individuals with obesity and T2DM. There are some limitations that complicate these conclusions; specifically, methodological differences between the present study, Brown and Stein (in preparation), and Epstein et al. (2022) make direct comparisons of outcome variables difficult. Despite these differences, no effects of EFT were observed on demand for exercise, self-reported weekly walking duration or accelerometer measured physical activity, HbA1c, or BMI in any of the three studies. Additionally, the present study is preliminary (i.e., study enrollment is ongoing), reducing power to detect a difference between outcomes of interest. However, we note that the estimate of the difference between the estimated marginal means was small, suggesting a clinically insignificant effect of EFT on α and $Q_{1\%}$ at each assessment session. Relatedly, the study was powered to detect an effect of EFT on the co-primary outcomes of BMI and HbA1c, not exercise demand. To elucidate the conditions (if any) in which EFT may function as a useful clinical tool, future research should seek to understand the interactions between EFT, delay discounting, and proven behavioral strategies for weight loss (e.g., self-monitoring of weight, increased physical activity; Varkevisser et al., 2019). Although EFT appeared to be a promising tool for adults with obesity or T2DM in early-stage work, successful translation may be moderated by a variety of variables, including the specific components of a given behavioral intervention utilized in combination with EFT, and the clinical population under study.

Tables and Figures

Table 1

Participant demographics by group

Baseline Demographics

Characteristic	EFT, N = 35[1]	HHT, N = 36[1]
Age	52.77 (10.12)	53.64 (12.00)
BMI	39.10 (5.60)	38.74 (6.57)
HbA1c	9.10 (1.34)	9.15 (1.23)
Race		
Black	9 / 35 (26%)	5 / 36 (14%)
White	26 / 35 (74%)	31 / 36 (86%)
Ethnicity		
No, not Hispanic or Latino	35 / 35 (100%)	35 / 36 (97%)
Yes, Hispanic or Latino	0 / 35 (0%)	1 / 36 (2.8%)
Education		
8th grade or less	0 / 35 (0%)	0 / 36 (0%)
Some High School	1 / 35 (2.9%)	0 / 36 (0%)
High School Graduate/Equivalent	4 / 35 (11%)	7 / 36 (19%)
Some College	9 / 35 (26%)	4 / 36 (11%)
College Graduate/2-year Degree	8 / 35 (23%)	9 / 36 (25%)
College Graduate/4-year Degree	8 / 35 (23%)	7 / 36 (19%)
Graduate or Professional Degree	5 / 35 (14%)	9 / 36 (25%)
Income		
$0 to $9,999	3 (8.6%)	3 (8.3%)
$10,000 to $19,999	4 (11%)	4 (11%)
$20,000 to $29,999	2 (5.7%)	4 (11%)
$30,000 to $39,999	1 (2.9%)	2 (5.6%)
$40,000 to $49,999	8 (23%)	5 (14%)
$50,000 to $59,999	6 (17%)	2 (5.6%)
$60,000 to $69,999	3 (8.6%)	4 (11%)
$70,000 to $79,999	3 (8.6%)	4 (11%)
$80,000 to $89,999	3 (8.6%)	4 (11%)
$90,000 to $99,999	1 (2.9%)	1 (2.8%)
$110,000 to $119,999	0 (0%)	2 (5.6%)
$140,000 to $149,999	1 (2.9%)	0 (0%)
$160,000 to $169,999	0 (0%)	1 (2.8%)
Gender		
Male	8 / 35 (23%)	12 / 36 (33%)
Female	27 / 35 (77%)	24 / 36 (67%)
Other (please specify)	0 / 35 (0%)	0 / 36 (0%)

[1] Mean (SD); n / N (%); n (%)

Figure 1

Study Intervention and Assessment Timeline

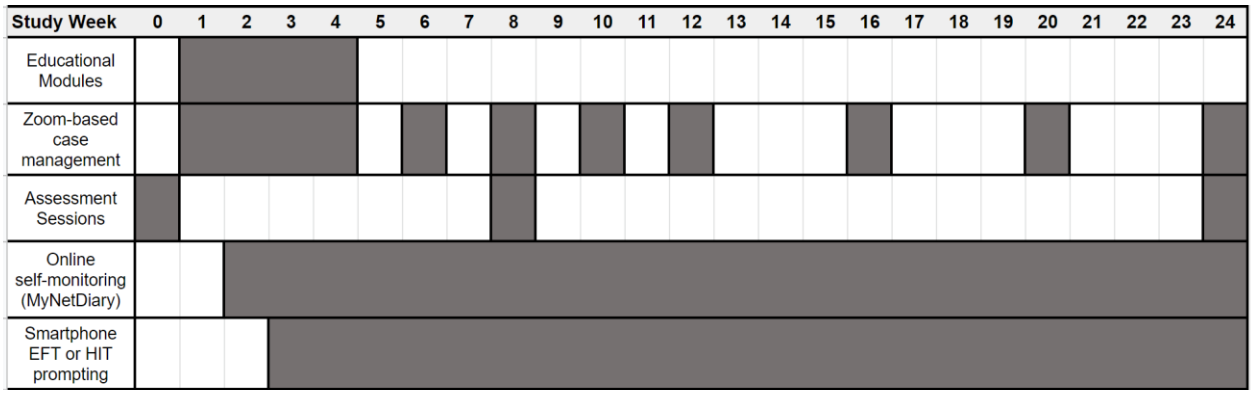
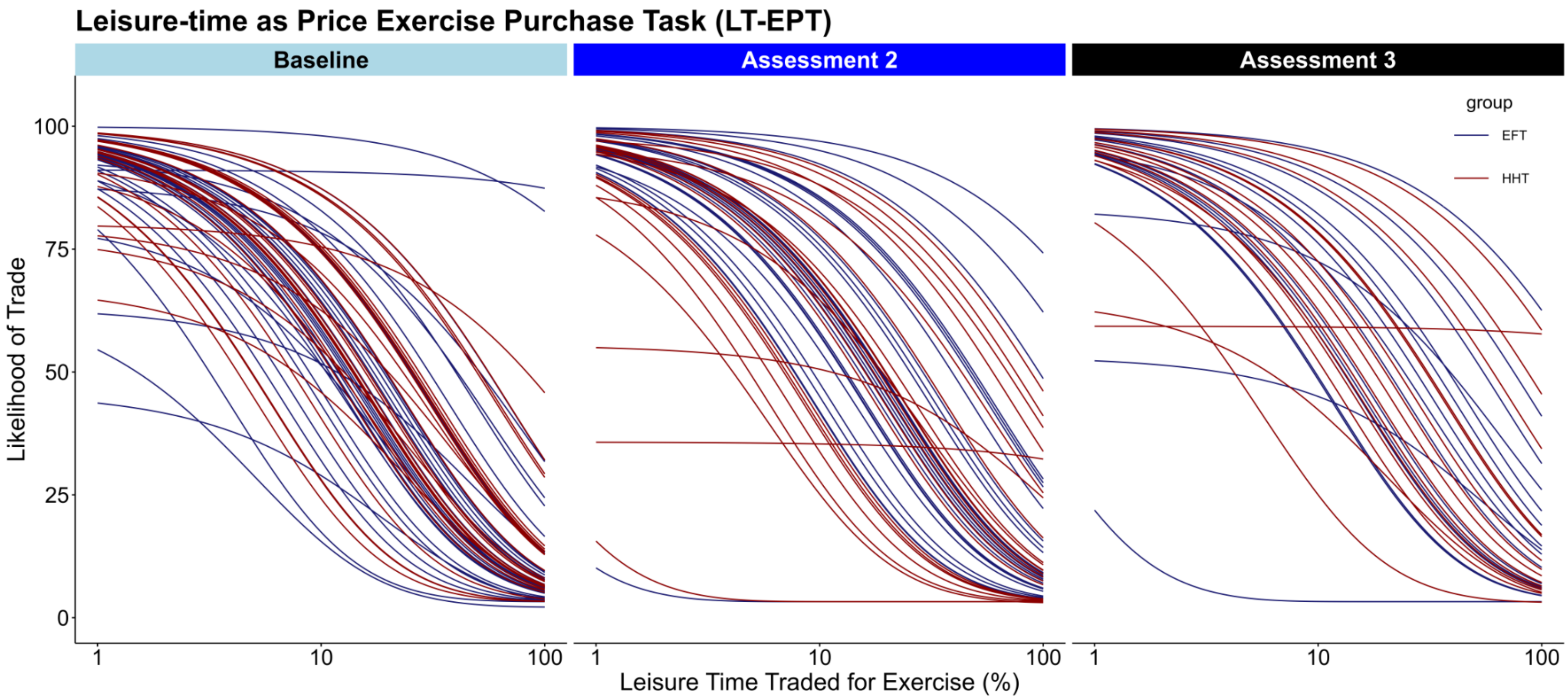


Figure 2

Model estimated exercise demand for EFT and HIT participants across assessment sessions



Note: Figure does not include non-systematic demand responses (see Results section for *n* excluded per group and session)

Table 2

Linear mixed-effects model results for log-transformed LT-EPT alpha

Linear mixed-effects model results - Alpha

	Alpha				
Predictors	*Estimates*	*std. Error*	*CI*	*p*	*df*
Intercept	-9.03	0.22	-9.47 – -8.59	**<0.001**	110.71
Group (EFT)	0.05	0.31	-0.58 – 0.67	0.885	107.12
Assessment 2 (Week 8)	-0.07	0.26	-0.59 – 0.46	0.803	80.12
Assessment 3 (Week 24)	-0.39	0.30	-0.98 – 0.21	0.203	83.83
Group (EFT) x Assessment 2 (Week 8)	-0.04	0.36	-0.75 – 0.67	0.909	75.66
Group (EFT) x Assessment 3 (Week 24)	0.25	0.42	-0.57 – 1.08	0.544	80.45
Random Effects					
σ^2	0.79				
$\tau_{00\ id}$	0.72				
ICC	0.48				
N_{id}	67				
Observations	143				
Marginal R^2 / Conditional R^2	0.010 / 0.483				
AIC	-2125.095				

Figure 3

Boxplot of log-transformed LT-EPT alpha values by group and session

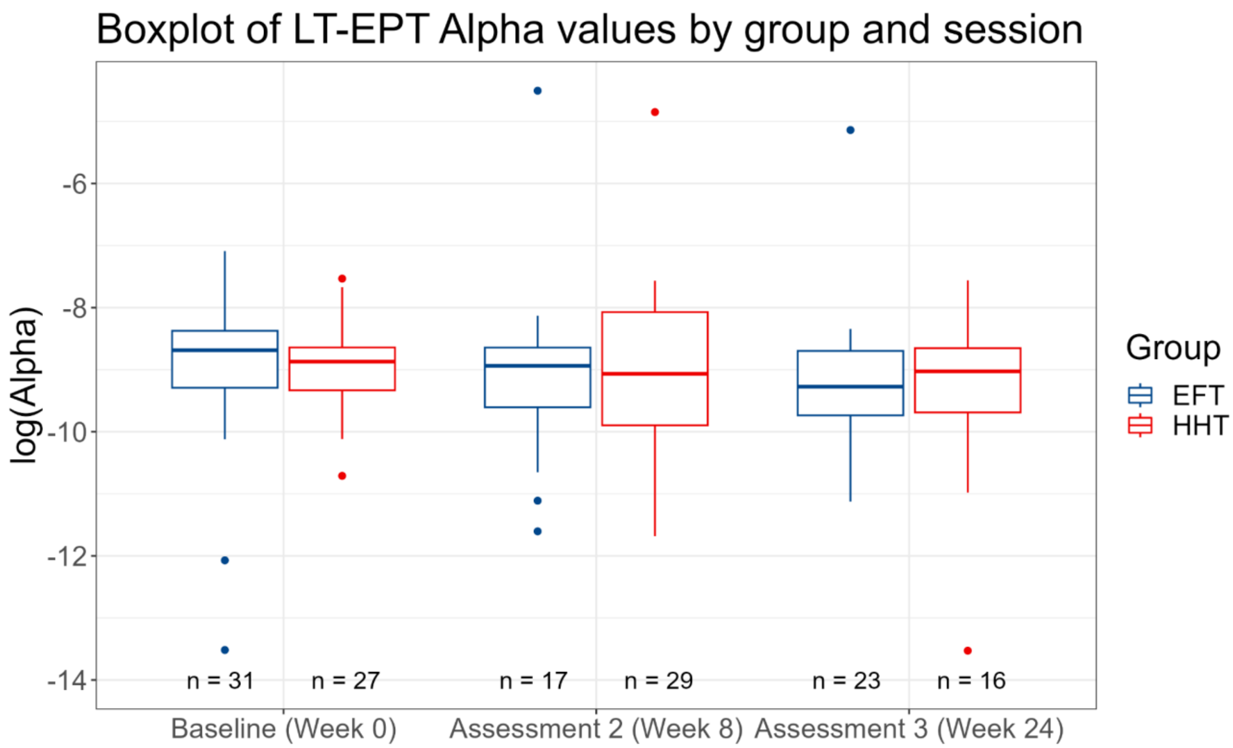


Table 3

Planned contrasts of group differences in estimated marginal means of log-transformed LT-EPT alpha across sessions

Contrast	Estimate	Std. Error	*df*	Statistic	*p*	*p* Bonf.
HHT Week 0 - EFT Week 0	-0.046	0.320	121.032	-0.143	0.887	1.000
HHT Week 8 - EFT Week 8	-0.005	0.346	131.515	-0.013	0.989	1.000
HHT Week 24 - EFT Week 24	-0.299	0.408	147.691	-0.733	0.464	1.000

Figure 4

Estimated marginal means of log-transformed LT-EPT alpha by group and session

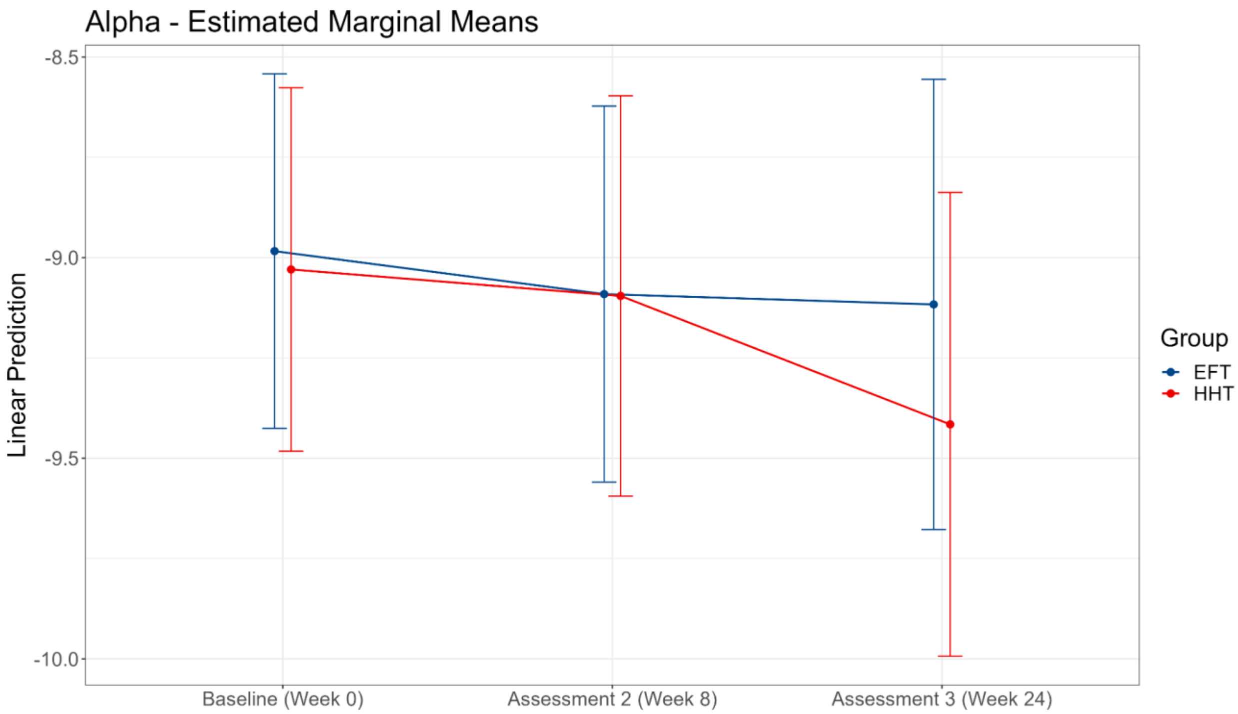


Table 4

Linear mixed-effects model results for LT-EPT $Q_{1\%}$

Linear mixed-effects model results - Q1e

	Q1%				
Predictors	*Estimates*	*std. Error*	*CI*	*p*	*df*
Intercept	92.57	3.45	85.75 – 99.40	**<0.001**	128.99
Group (EFT)	-3.87	4.82	-13.40 – 5.66	0.423	126.91
Assessment 2 (Week 8)	-5.96	4.29	-14.46 – 2.55	0.168	101.84
Assessment 3 (Week 24)	-6.87	4.76	-16.32 – 2.58	0.152	104.87
Group (EFT) x Assessment 2 (Week 8)	10.26	5.82	-1.30 – 21.82	0.081	97.58
Group (EFT) x Assessment 3 (Week 24)	5.64	6.67	-7.58 – 18.86	0.399	102.38
Random Effects					
σ^2	212.43				
$\tau_{00\ id}$	142.24				
ICC	0.40				
N_{id}	67				
Observations	144				
Marginal R^2 / Conditional R^2	0.022 / 0.414				
AIC	1227.569				

Figure 5

Boxplot of LT-EPT $Q_{1\%}$ values by group and session

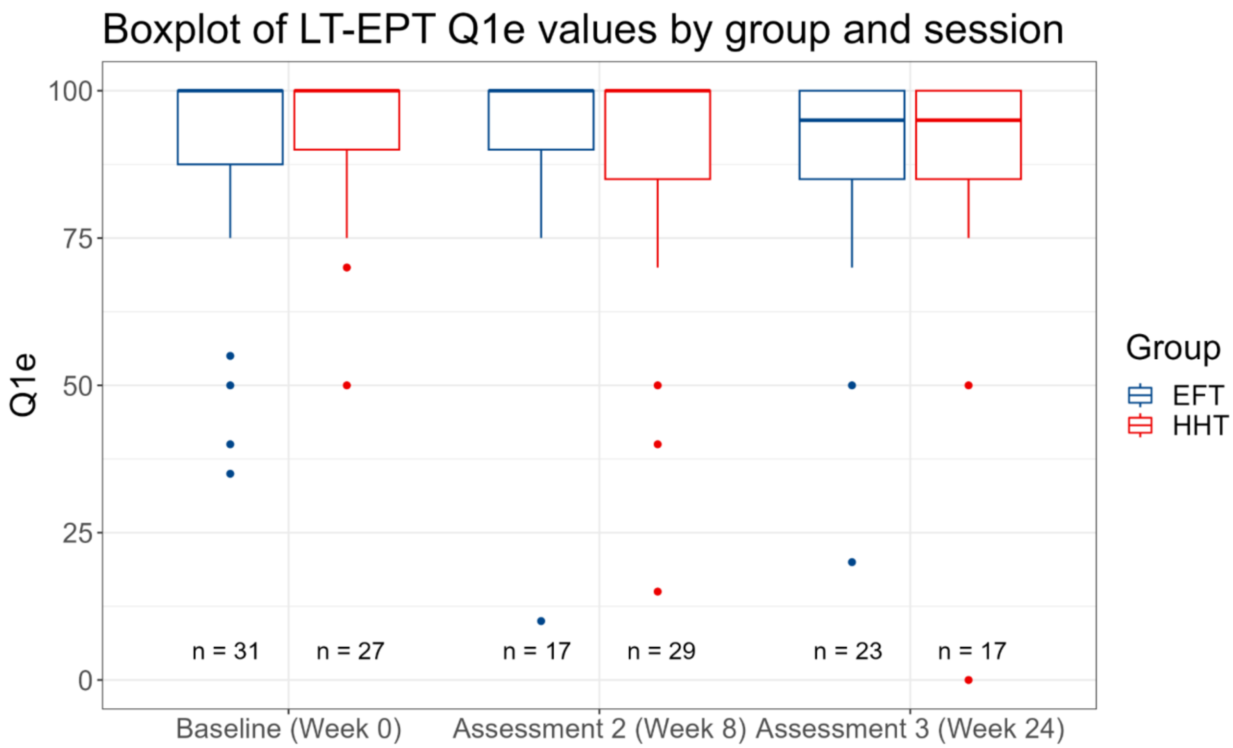


Table 5

Planned contrasts of group differences in estimated marginal means of LT-EPT $Q_{1\%}$ across sessions

Contrast	Estimate	Std. Error	*df*	Statistic	*p*	*p* Bonf.
HHT Week 0 - EFT Week 0	3.873	4.919	129.684	0.787	0.433	1.000
HHT Week 8 - EFT Week 8	-6.388	5.352	137.985	-1.194	0.235	0.704
HHT Week 24 - EFT Week 24	-1.767	6.293	149.500	-0.281	0.779	1.000

Figure 6

Estimated marginal means of LT-EPT $Q_{1\%}$ by group and session

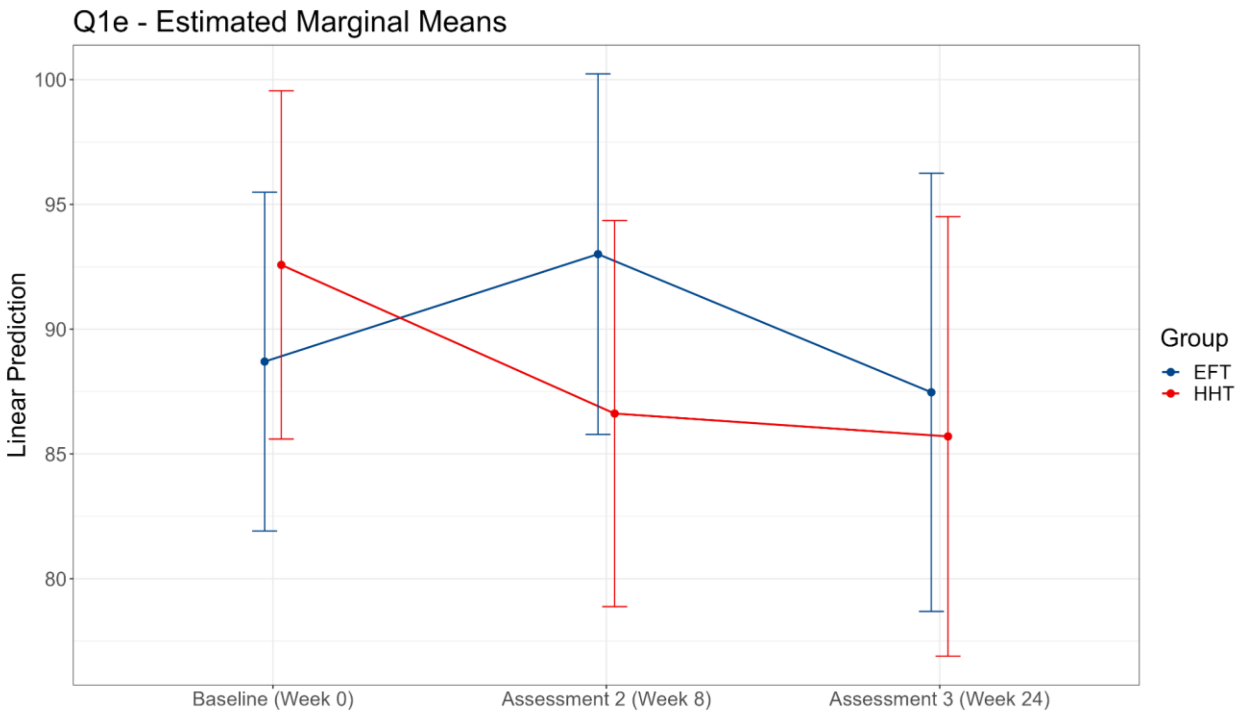


Table 6

Linear mixed-effects model results for square-root transformed weekly walking minutes

Linear mixed-effects model results - Weekly walking mins

	Square-root transformed weekly walking mins				
Predictors	*Estimates*	*std. Error*	*CI*	*p*	*df*
Intercept	15.85	2.30	11.30 – 20.39	**<0.001**	115.15
Group (EFT)	-0.89	3.27	-7.37 – 5.59	0.786	115.15
Assessment 2 (Week 8)	2.14	2.59	-3.02 – 7.29	0.412	93.78
Assessment 3 (Week 24)	1.65	2.94	-4.18 – 7.48	0.575	98.25
Group (EFT) x Assessment 2 (Week 8)	0.34	3.63	-6.87 – 7.54	0.927	92.42
Group (EFT) x Assessment 3 (Week 24)	-2.60	4.24	-11.02 – 5.83	0.542	98.17
Random Effects					
σ^2	100.39				
$\tau_{00\ id}$	89.43				
ICC	0.47				
N_{id}	71				
Observations	167				
Marginal R^2 / Conditional R^2	0.010 / 0.476				

Figure 7

Boxplot of square-root transformed weekly walking minutes

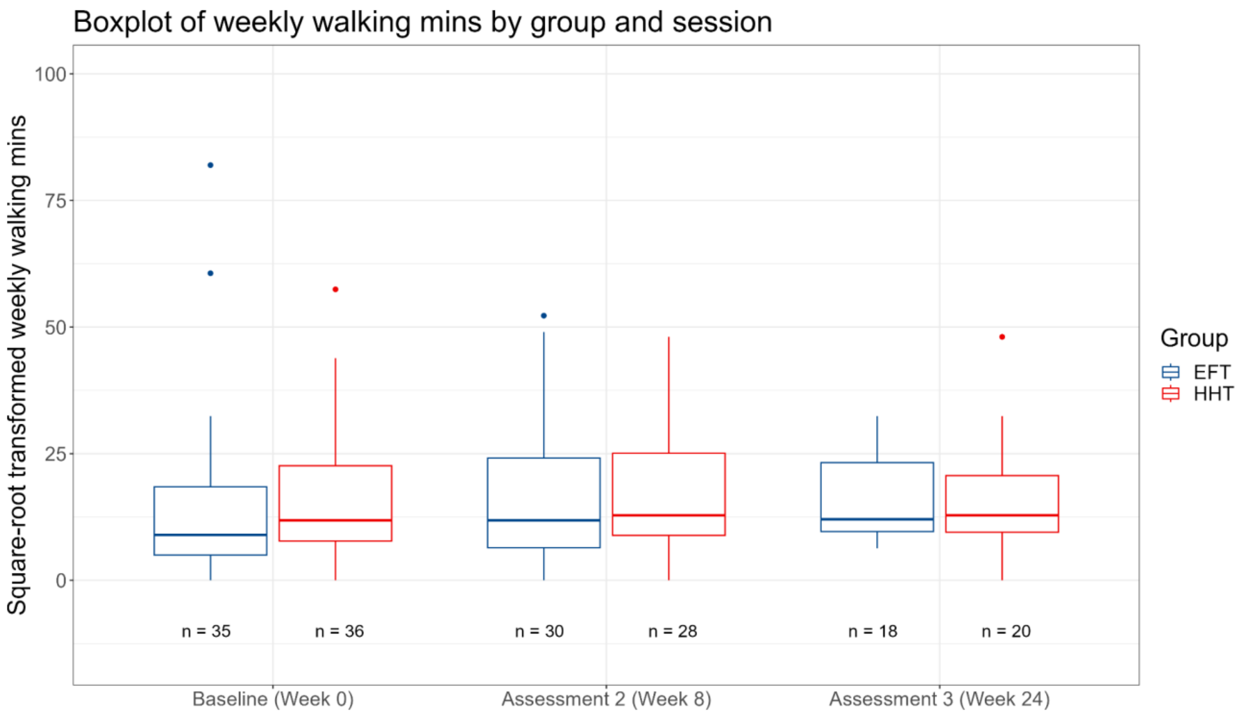


Table 7

Planned contrasts of group differences in estimated marginal means of square-root transformed weekly walking minutes

Contrast	Estimate	Std. Error	*df*	Statistic	*p*	*p* Bonf.
HHT Week 0 - EFT Week 0	0.890	3.326	128.706	0.268	0.789	1.000
HHT Week 8 - EFT Week 8	0.555	3.609	143.971	0.154	0.878	1.000
HHT Week 24 - EFT Week 24	3.487	4.258	168.593	0.819	0.414	1.000

Figure 8

Estimated marginal means of square-root transformed weekly walking minutes

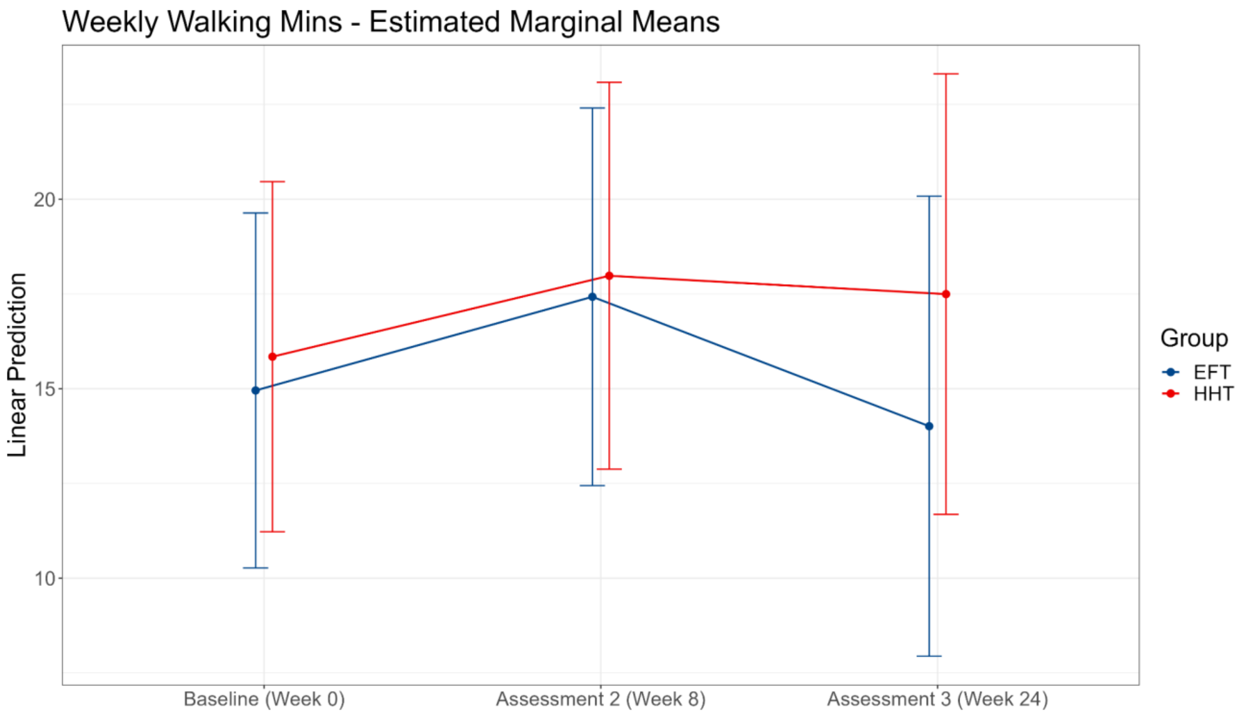


Table 8

Linear mixed-effects model results for ordinal AUC

Linear mixed-effects model results - ordinal AUC

	ordinal AUC				
Predictors	*Estimates*	*std. Error*	*CI*	*p*	*df*
Intercept	0.63	0.04	0.56 – 0.70	**<0.001**	113.18
Group (EFT)	-0.03	0.05	-0.13 – 0.07	0.598	113.18
Assessment 2 (Week 8)	0.10	0.04	0.02 – 0.17	**0.010**	101.62
Assessment 3 (Week 24)	0.08	0.04	-0.01 – 0.16	0.073	104.92
Group (EFT) x Assessment 2 (Week 8)	0.02	0.05	-0.08 – 0.12	0.710	100.48
Group (EFT) x Assessment 3 (Week 24)	-0.03	0.06	-0.15 – 0.09	0.588	104.75
Random Effects					
σ^2	0.02				
$\tau_{00\ id}$	0.02				
ICC	0.55				
N_{id}	71				
Observations	167				
Marginal R^2 / Conditional R^2	0.053 / 0.569				
AIC	-37.735				

Figure 9

Boxplot of ordinal AUC values by group and session

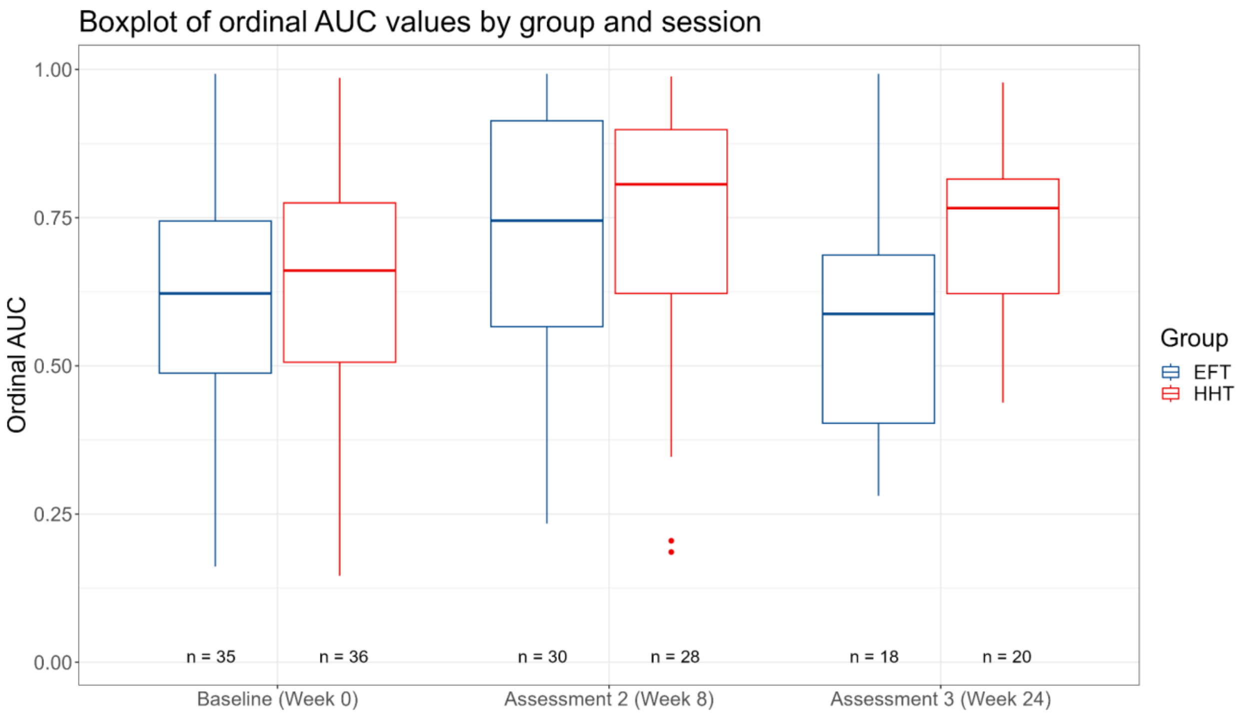


Table 9

Planned contrasts of group differences in estimated marginal means of ordinal AUC across sessions

Contrast	Estimate	Std. Error	*df*	Statistic	*p*	*p* Bonf.
HHT Week 0 - EFT Week 0	0.027	0.051	119.151	0.520	0.604	1.000
HHT Week 8 - EFT Week 8	0.007	0.055	135.598	0.132	0.895	1.000
HHT Week 24 - EFT Week 24	0.060	0.064	164.507	0.933	0.352	1.000

Figure 10

Estimated marginal means of ordinal AUC by group and session

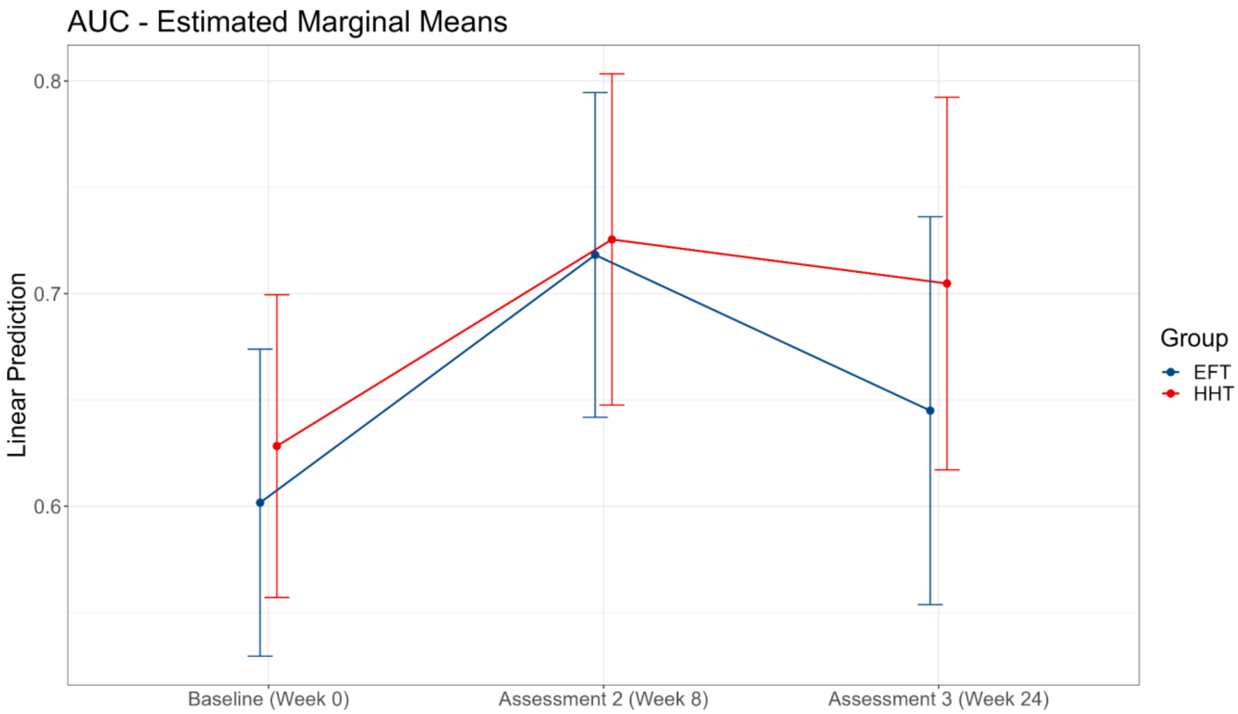


Table 10

Linear mixed-effects model results for HbA1c

Linear mixed-effects model results - HbA1c

	HbA1c				
Predictors	*Estimates*	*std. Error*	*CI*	*p*	*df*
Intercept	9.15	0.24	8.67 – 9.62	**<0.001**	91.86
Group (EFT)	-0.05	0.34	-0.73 – 0.63	0.890	91.86
Assessment 2 (Week 8)	-0.93	0.19	-1.30 – -0.56	**<0.001**	100.97
Assessment 3 (Week 24)	-0.98	0.21	-1.40 – -0.56	**<0.001**	102.18
Group (EFT) x Assessment 2 (Week 8)	0.25	0.26	-0.26 – 0.76	0.340	100.36
Group (EFT) x Assessment 3 (Week 24)	0.16	0.30	-0.44 – 0.77	0.590	101.97
Random Effects					
σ^2	0.50				
$\tau_{00\ id}$	1.58				
ICC	0.76				
N_{id}	71				
Observations	167				
Marginal R^2 / Conditional R^2	0.080 / 0.780				
AIC	529.377				

Figure 11

Boxplot of HbA1c values by group and session

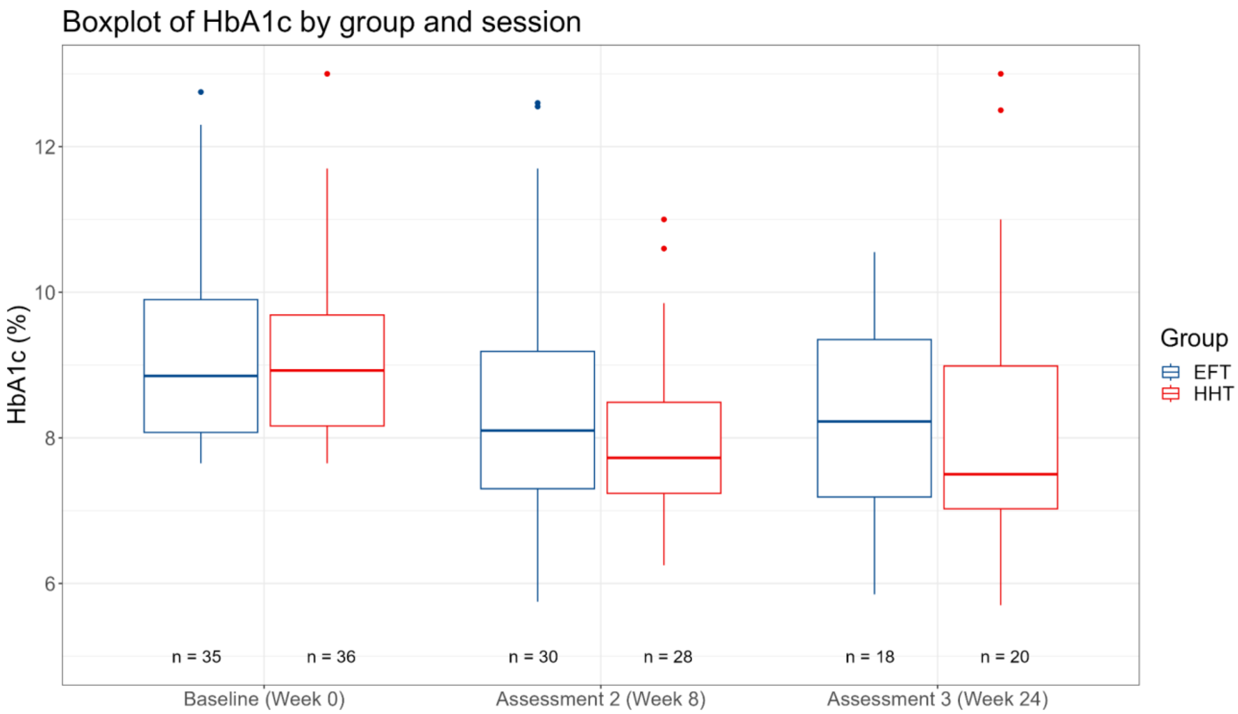


Table 11

Planned contrasts of group differences in estimated marginal means of HbA1c across sessions

Contrast	Estimate	Std. Error	*df*	Statistic	*p*	*p* Bonf.
HHT Week 0 - EFT Week 0	0.047	0.348	94.054	0.136	0.892	1.000
HHT Week 8 - EFT Week 8	-0.201	0.364	107.026	-0.552	0.582	1.000
HHT Week 24 - EFT Week 24	-0.117	0.399	135.687	-0.294	0.769	1.000

Figure 12

Estimated marginal means of HbA1c by group and session

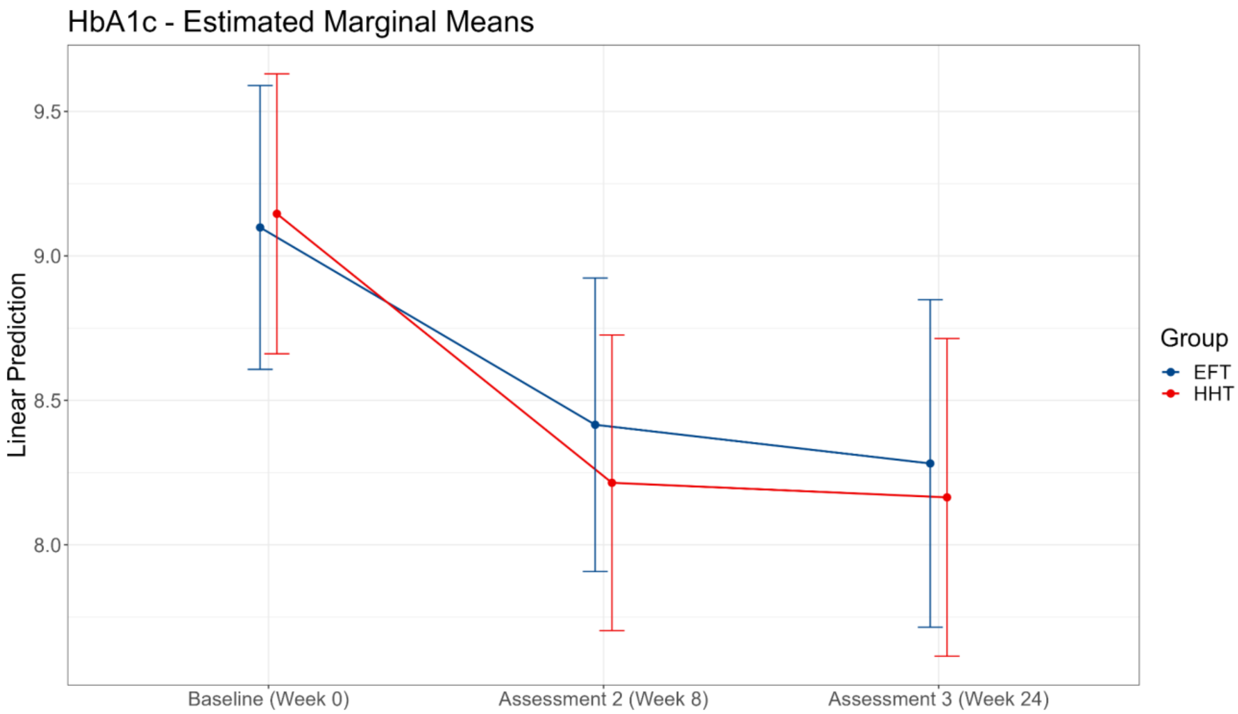


Table 12

Linear mixed-effects model results for BMI

Linear mixed-effects model results - BMI

	BMI				
Predictors	*Estimates*	*std. Error*	*CI*	*p*	*df*
Intercept	38.74	1.01	36.72 – 40.75	**<0.001**	72.86
Group (EFT)	0.37	1.44	-2.51 – 3.24	0.799	72.86
Assessment 2 (Week 8)	-1.27	0.26	-1.78 – -0.76	**<0.001**	96.50
Assessment 3 (Week 24)	-1.99	0.29	-2.58 – -1.41	**<0.001**	96.59
Group (EFT) x Assessment 2 (Week 8)	-0.18	0.36	-0.89 – 0.53	0.624	96.44
Group (EFT) x Assessment 3 (Week 24)	-0.18	0.42	-1.01 – 0.66	0.680	96.56
Random Effects					
σ^2	0.93				
$\tau_{00\ id}$	35.98				
ICC	0.97				
N_{id}	71				
Observations	167				
Marginal R^2 / Conditional R^2	0.020 / 0.975				
AIC	794.023				

Figure 13

Boxplot of BMI values by group and session

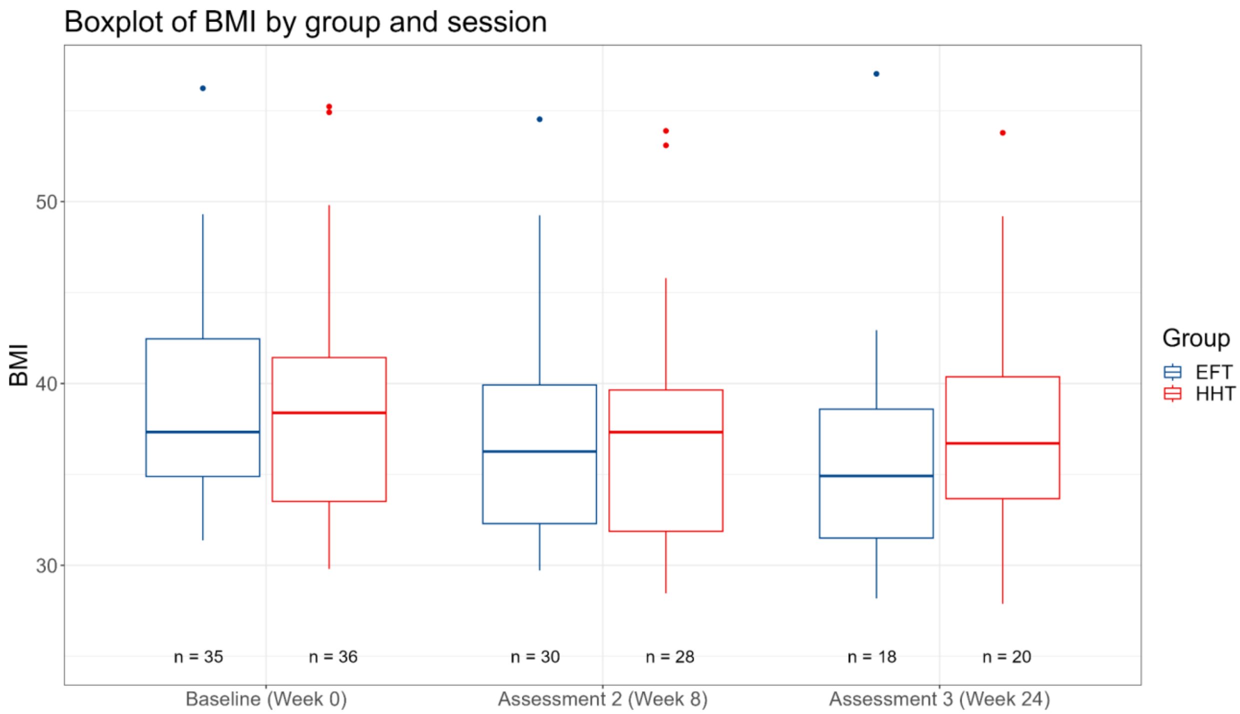


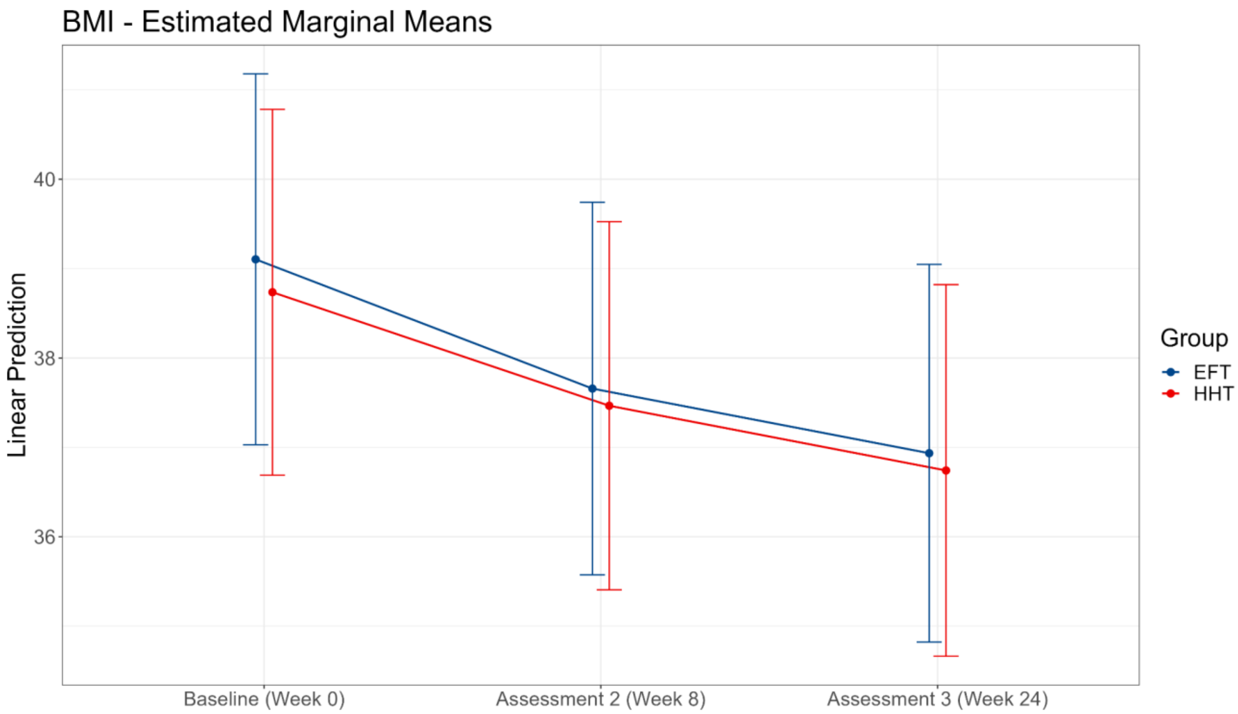
Table 13

Planned contrasts of group differences in estimated marginal means of BMI across sessions

Contrast	Estimate	Std. Error	*df*	Statistic	*p*	*p* Bonf.
HHT Week 0 - EFT Week 0	-0.368	1.463	74.950	-0.252	0.802	1.000
HHT Week 8 - EFT Week 8	-0.192	1.471	76.563	-0.131	0.896	1.000
HHT Week 24 - EFT Week 24	-0.193	1.489	80.198	-0.130	0.897	1.000

Figure 14

Estimated marginal means of BMI by group and session



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