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Review article

# Temporal discounting as a candidate behavioral marker of obesity

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ABSTRACT

Although obesity is a result of processes operating at multiple levels, most forms result from decision-making behavior. The aim of this review was to examine the candidacy of temporal discounting (TD) (i.e. the reduction in the value of a reinforcer as a function of the delay to its receipt) as a behavioral marker of obesity. For this purpose, we assessed whether TD has the ability to: identify risk for obesity development, diagnose obesity, track obesity progression, predict treatment prognosis/outcomes, and measure treatment effectiveness. Three databases (Pubmed, PsycINFO, and Web of Science) were searched using a combination of terms related to TD and obesity. A total of 153 papers were reviewed. Several areas show strong evidence of TD's predictive utility as a behavioral marker of obesity (e.g., distinguishing obese from non obese). However, other areas have limited and/or mixed evidence (e.g., predicting weight change). Given the positive relationship for TD in the majority of domains examined, further consideration for TD as a behavioral marker of obesity is warranted.

## 1. Introduction

The search for and identification of biomarkers have been an area of growing scientific emphasis. For example, the search term "biomarkers" in PubMed returns over 4000 papers published in 2020. Biomarkers have been defined as: "A characteristic that is objectively measured and evaluated as an indicator of normal biological processes, pathogenic processes, or pharmacologic responses to a therapeutic intervention." (Biomarkers Definitions Working Group, 2001, p. 89). In principle, biomarkers, if identified, could be useful in a variety of ways. A valid biomarker could serve a variety of functions including: the identification of those at risk for disease development, disease diagnosis, classification of disease progression, predict treatment prognosis/outcomes, and measure treatment effectiveness (Biomarkers Definitions Working Group, 2001; FDA-NIH Biomarker Working Group, 2016). Some have recently suggested that the future identification of biomarkers may entail big data and machine learning to screen thousands of molecular components (Singh, 2019; Zeng et al., 2016).

Similar suggestions have been presented in obesity science, focusing on inflammation processes (Nimptsch et al., 2019; Shi and Max Goodson, 2019). The results of these efforts will await new findings. However, unlike other diseases, obesity results from a higher level of integrative function. Although obesity entails a variety of processes operating at multiple levels, most forms result from behavior, be it the decision to eat, what to eat, how much to eat, or how much to engage in vigorous activity (Epstein et al., 2018; Trivedi et al., 2015). Indeed, most forms of obesity would not occur if not for the behavior mentioned above. As such, biomarkers may be evident in behavior. Moreover, a viable behavioral marker may be able to identify specific phenotypes related to obesity (e.g., Carr and Kraft, 2018).

One potential behavioral candidate is temporal discounting (TD), a neurobehavioral process derived from behavioral economics and studied in neuroeconomics (Bickel et al., 2007; Green and Myerson, 2004; Madden and Bickel, 2010). TD refers to the reduction in the value of a reinforcer as a function of the delay to its receipt (Green and Myerson, 2004; Madden and Johnson, 2010). Usual methods entail presenting a choice between two monetary alternatives, with one option being a smaller, more immediate amount of money, and the other a more substantial later amount (see Box 1 for more details). A similar construct we will review here is delay of gratification, a measure frequently used with children. Delay of gratification is assessed by offering children a small reward available immediately, often an edible item or toy, or a larger reward available after a delay (see Box 1 for more details). Excessive TD has been demonstrated in various disorders, and as a result, is

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considered a trans-disease process (Bickel et al., 2019, 2012b). Moreover, TD has been identified as a candidate behavioral marker in addiction (Bickel et al., 2014b; Kwako et al., 2018). In the field of obesity science, since the first research report of excessive TD in 2008 (Weller et al., 2008), a sufficient number have been published to support a meta-analysis (Amlung et al., 2016).

Here we assess the candidacy of TD as a behavioral marker of obesity (NIH Health Topics, 2019), defined as having a body mass index (BMI) of 30 or greater. Although several reviews of discounting and obesity have been conducted, to date none have examined whether discounting can function as a behavioral marker in obesity (Amlung et al., 2016; Barlow et al., 2016; McClelland et al., 2016; Stojek et al., 2014; Tang et al., 2019). Thus, we will review the research on TD in obesity, focusing primarily on human studies of monetary discounting, since such a version is the most widely used. We will organize this review by addressing the potential utility of a marker outlined by the NIH Biomarkers working group (Biomarkers Definitions Working Group., 2001). Specifically, we will examine whether this measure identifies those at risk for developing obesity, can diagnose obesity, tracks disease progression, predicts treatment prognosis/outcomes, and measures treatment effectiveness. Not all these areas have been extensively investigated, and thus, the assessment of some of these domains may be more provisional and will await further study for more definitive estimates. Although TD has been considered a measure of impulsivity, reviewing other putative measures of multi-faceted impulsivity construct is beyond this review's scope (c.f. Bickel et al., 2012a; Strickland and Johnson, 2020).

## 2. Search strategy

In order to identify the target literature, a search of Pubmed, Web of Science and PsycINFO was conducted to capture citations relevant to TD and obesity. A combination of the terms related to 'discounting' and 'obesity' were searched (i.e., (obesity OR overweight OR "body mass index" OR "weight gain") AND ("intertemporal preferences" OR "time preference" OR "delayed gratification" OR "delay* gratification" OR "delay of gratification" OR discounting)). The search time window was from inception to November 2020. The search resulted in 1094 citations related to TD and obesity; 761 after removing duplicates. The titles and abstracts of the citations were reviewed according to the inclusion

**Box 1**
Temporal Discounting.

**Temporal discounting** is the process by which a reward loses value as a function of the delay to its receipt (Ainslie, 1975; Rachlin and Green, 1972). Procedures to measure this process entail choosing between a smaller, immediately available reward and a larger reward available after a delay.

**Delay of gratification** tasks have been used to study self-control in children and adolescents (Mischel et al., 1989). In this paradigm, children are placed in an environment where a preferred reward (foodstuff, toy) is available after a delay or a less preferred reward is available immediately.

Temporal discounting is often assessed via monetary incentive tasks, where individuals choose between a smaller amount of money, available immediately, or a larger amount available after a delay. These tasks can involve making repeated choices over many trials or a just a few trials (e.g., two trial task). The former requires more time but allows for a more granular assessment of valuation while the latter is quicker but gives a coarser estimate of valuation. Neuroimaging investigations have utilized brief tasks to investigate neural correlates of intertemporal choice between "easy" and "hard" choices (based upon a participant's preference for immediate or delayed rewards).

A commonly used method is the **adjusting-amount task** (Du et al., 2002). In this task, individuals repeatedly choose between a smaller amount of money, available immediately, and a larger amount available after a delay (e.g., $50 now or $100 in one week). During this procedure the larger amount remains constant while the smaller amount titrates up or down, based upon the prior choice, until the individual is indifferent between the two. At this **indifference point** the subjective value of the two rewards is approximately equal. This procedure is repeated across multiple delays (e.g., 1 day, 1 week, 1 month, 3 months, 1 year, 5 years, 25 years) to obtain additional indifference points which are then plotted to obtain a discounting curve (i.e., discounted reward value as a function of delay to receipt).

The calculation of indifference points allows fitting to a non-linear regression model. A plethora of methods to account for discounting have been proposed (for review see (Franck et al., 2019)) Mazur's hyperbolic model (Mazur, 1987)

$$SV = \frac{A}{1 + kD} \quad (1)$$

is often used in both the obesity (Amlung et al., 2016) and addiction literature (MacKillop et al., 2011). In Eq. 1, SV is the subjective value of the reward, A is the nominal, full magnitude value of the reward, D is the delay to reward receipt, and $k$ is a free parameter which indexes the discounting rate. Higher values of $k$ indicate a more rapid decline in the value of the delayed reward (Odum, 2011b).

Two Criteria have been developed to identify **non-systematic responses** in discounting tasks in an effort to improve the quality of data collected: 1) starting with the second delay, if any indifference point is greater than the preceding indifference point by a magnitude greater than 20 % of the delayed reward, and 2) if the final indifference point is not less than the first indifference point by at least a magnitude equal to 10 % of the delayed reward. Violation of criterion 1 suggests that further delay causes reward value to increase rather than decrease, while violation of criterion 2 suggests that delay has no effect on reward value (Johnson and Bickel, 2008). Violations of either criterion call into question the validity of the data and merit consideration for exclusion from analyses.

An additional method to interpret temporal discounting data is using **area under the curve (AUC).** This method entails calculating the area under the discounting curve to yield a value from 0 to 1, with higher **AUC** indicating greater value of future monetary rewards.

Several tasks have been developed to provide a quicker method of $k$ value estimation. The **monetary choice questionnaire** (MCQ; Kirby et al., 1999) is an adjusting amount task that assesses an individual's pattern of choices across 27 questions to assign one of ten discrete $k$ values. In an **adjusting delay task,** individuals are presented with a choice between an immediately available smaller reward and a larger reward available after a delay (e.g., $500 now or $1000 in 3 weeks). Across five trials the monetary choices remain constant while the delay changes, allowing for estimation of $k$ in less than one minute (Koffarnus and Bickel, 2014).

criteria listed below:

i Used a measure of 'temporal discounting' (i.e., monetary delay discounting in adults or 'delay of gratification' in child samples).
ii Reported a measure of 'obesity' (e.g., overweight/obese sample defined by body mass index or body fat percentage) or a measure associated with 'obesity' (e.g., body mass index, body fat percentage, weight change, energy intake, physical activity).
iii Tested for an association between 'temporal discounting' and measures of or associated with 'obesity'.
iv Human study.
v Peer-reviewed.
vi English language.
vii Full-text available.

Of those, 553 citations were excluded after reviewing the abstract and 59 citations were removed after review of the full text for not meeting the parameters for this review. Finally, we checked the reference lists of studies identified during this search, as well as already existing reviews, in order to identify additional studies. Four other studies were included. The final sample consisted of 153 studies (see Table 1 for a summary of the studies).

## 3. Risk for disease development

One measure of a biomarker's utility is its ability to identify those at risk for disease development. Here, we explore the use of TD as a biomarker to identify those at risk for the development of obesity. First, we consider longitudinal studies that examine the ability of TD assessed early in life to predict later weight gain and onset of obesity. Second, we consider the relationship of TD to maladaptive health behaviors that promote obesity, such as the increased consumption of highly palatable foods, decreased engagement in physical activities, and lack of sleep.

### 3.1. Prediction of obesity onset

The relationship between TD and obesity onset can be assessed using longitudinal studies measuring TD rate and BMI at a time point prior to the onset of obesity (i.e., during childhood or adolescent years) and following up at a later date to ascertain which individuals eventually became obese. To our knowledge, no studies to date have assessed TD's ability to predict obesity onset. However, seven studies assessed the association between delay of gratification (a similar construct to TD; see Box 1) and obesity onset/high weight gain among toddlers and young children. Those studies indicated that children's performance on delay of gratification tasks is associated longitudinally with obesity onset and/or their weight (Connell and Francis, 2014; Duckworth et al., 2013; Evans et al., 2012; Francis and Susman, 2009; Graziano et al., 2010; Schlam et al., 2013; Seeyave et al., 2009). First, a study by Seeyave et al. (2009) indicated that children with poorer performance on a delay of gratification task at age 4 were more likely to be overweight at age 11. The association between task performance and BMI at age 11, however, was partially explained by maternal weight status (maternal weight status reduced the association significantly). Second, Francis and Susman (2009) indicated that those who scored high on delay of gratification tasks at ages 3 and 5 had lower BMIs and fewer increases in BMI through age 12 compared to those who scored low on the same tasks. Third, as reported by Graziano et al. (2010), ability to delay gratification at age 2 predicted pediatric obesity at age 5 even after controlling for BMI at baseline. Fourth, Schlam et al. (2013) reported that those who delayed gratification longer at age 4 had a significantly lower BMI 30 years later. Fifth, Duckworth et al. (2013) indicated that children who delayed gratification longer at age 4 had healthier BMI scores at age 14. Sixth, a study by Evans et al. (2012) reported that delay of gratification mediates the association between cumulative risk (calculated across children's exposure to nine sociodemographic, physical, and psychological risk factors at age 9) and gains in BMI four years later (i.e., at age 13). And finally, Connell and Francis (2014) reported a significant interaction effect of parenting style and ability to delay gratification on BMI growth trajectories for boys from ages 4–15 years independent of pubertal status, mother's education, and family income-to-needs ratio. The effect of delay of gratification on BMI growth indicates that, over time, boys who can delay gratification have less BMI growth compared to those who fail to delay gratification. For girls, however, the only significant predictor of differences in the rate of growth in BMI from 4 to 15 years was time.

Together, these initial findings demonstrate that obesity could be prospectively predicted by inherent or preexisting differences in choices between immediate and delayed rewards. Delay of gratification, a construct similar to TD, appears to be a reliable predictor of obesity onset in children, however, since TD cannot be measured in young children it has not been specifically used as a predictor among this population. Further research among older children or young adults is required to ascertain TD's predictive utility. If TD reliably predicts obesity onset, it could help identify and target individuals at greater risk of developing obesity and would support the classification of TD as a candidate behavioral marker of obesity. Further longitudinal research among older children or young adults using TD specifically is needed to confirm these research findings on this prospective relationship in the obese population.

### 3.2. Relationship to energy consumed and expended

Obesity results from a combination of maladaptive health behaviors including overconsumption of calories and under engagement in physical activity (Basile et al., 2019; Brytek-Matera et al., 2018; Kofman et al., 2010; Pietiläinen et al., 2008; Wiklund, 2016). Here we examine TD as a biomarker for eating and exercise behaviors that promote obesity.

#### 3.2.1. Energy consumption

A primary driver of overweight and obese outcomes is the consumption of calories beyond what is needed for an individual's Total Daily Energy Expenditure (TDEE), or the necessary energy needed to maintain body functioning (Drenowatz et al., 2015; Raymond et al., 2012). Over the past several decades, the development of highly processed foods has made calorically dense foods cheap and easily accessible. This change in the food industry has corresponded with an increase in the estimated total daily energy intake at an individual level as well as a more overweight and obese society (Swinburn et al., 2009). Here we examine the literature discussing the relationship between energy intake and TD.

Recent cross-sectional investigations have characterized the association between TD and food consumption or food purchasing behaviors. First, studies have shown that steep TD is related to lack of food label use while shopping, decreased consideration of food quality, and lack of available healthy foods in the home, which are all associated with unhealthy food consumption (Garza et al., 2019). Second, steep TD is associated with heightened consumption of fast food, high sugar foods, and otherwise unhealthy diets as well as increased levels of night eating, which are all associated with increased BMI (Barlow et al., 2016; Caleza-Jimenez et al., 2017; Garza et al., 2016; Malesza, 2020; Shuval et al., 2016). Steep TD also predicts non-adherence to a Mediterran Diet, a nutritionally balanced diet composed of fruits, vegetables, and fish (Howatt et al., 2019; Muñoz Torrecillas et al., 2018) as well as lower overall healthy eating (as assessed by analysis of food receipts) (Appelhans et al., 2019). Our lab has additionally shown that steep TD is associated with lower diet quality (as measured by 24 -h food recalls) and higher blood glucose levels (HbA1c) in a group of prediabetic adults who were also prescribed hypertension or dyslipidemia drugs (Epstein et al., 2020).

Another area of research has focused on the relationship between TD

**Table 1**
Studies reviewed by functions of a biomarker.

| Biomarker Criteria | Reference | Study Sample | Study Design | Study Location | Effect | Discounting task used | Magnitude | Sample Size |
|---|---|---|---|---|---|---|---|---|
| **Risk for disease development** | | | | | | | | |
| Prediction of obesity onset | Connell and Francis, 2014 | Children (4 years old) | Observational (Longitudinal) | National Survey | Yes | Delay of gratification | Animal crackers, pretzels OR M&M | 778 |
| | Duckworth et al., 2013 | Children (4 years old) | Observational (Longitudinal) | Laboratory | Yes | Delay of gratification | Several snacks (e.g., chocolate candies, cookies, pretzels) | 966 |
| | Evans et al., 2012 | Children (9 years old) | Observational (Longitudinal) | Home | Yes | Delay of gratification | Candy | 244 |
| | Francis and Susman, 2009 | Children (3 and 5 years old) | Observational (Longitudinal) | Home and laboratory | Yes | Delay of gratification | A toy or snacks (animal crackers, pretzels OR M&M) | 1061 |
| | Graziano et al., 2010 | Children (2 years old) | Observational (Longitudinal) | Laboratory | Yes | Delay of gratification | A gift | 57 |
| | Schlam et al., 2013 | Children (4 years old) | Observational (Longitudinal) | School and home | Yes | Delay of gratification | Snacks (e.g., cookies, marshmallows, or pretzels) | 164 |
| | Seeyave et al., 2009 | Children (4 years old) | Observational (Longitudinal) | National Survey | Yes | Delay of gratification | Candy, animal crackers, or pretzels | 805 |
| Relationship to energy consumed and expended<br>*Energy consumed* | Appelhans et al., 2011 [a] | Adult women (18–45) | Experimental (Acute) | Laboratory | Yes | Adjusting amount | $100 | 62 |
| | Appelhans et al., 2012 [a] | Adult women (18–45) | Observational (Longitudinal) | Natural environment | Yes | Adjusting amount | $100 | 78 |
| | Appelhans et al., 2019 | Adults | Observational (Longitudinal) | Home | Yes | Adjusting amount | $100 | 202 |
| | Bennett and Blissett, 2017 [a] | Children (2–4) | Experimental (Acute) | Laboratory | No | Delay of gratification | Chocolate buttons | 95 |
| | Bennett and Blissett, 2019 | Children (7–11) | Experimental (Acute) | Laboratory | Yes | Delay of gratification | Tokens for prizes | 50 |
| | Caleza-Jimenez et al., 2017 | Children (4–6) | Observational (Acute) | Laboratory | Yes | Delay of gratification | Candy | 202 |
| | Courtemanche et al., 2015 | Adolescents and adults (14–22, assessed again at 41–50) | Observational (Longitudinal) | Laboratory | Yes | Two questions to calculate discount factor | $1000 | 12,686 |
| | DeVoe et al., 2013 | Adults (45–49) | Observational (Acute) | National survey | Yes | One question regarding claiming of a prize | $1000 | 6111 |
| | Ely et al., 2015 | Adult women (18–30) | Experimental (Acute) | Laboratory | Yes | Adjusting amount | $100 | 78 |
| | Epstein et al., 2020 [a] | Adults | Obervational (Longitudinal) | Laboratory and home | Yes | Adjusting amount | $100; $1000 | 81 |
| | Epstein et al., 2014b | Adults | Observational (Acute) | Online | Yes | Adjusting amount | $1000 | 975 |
| | Fields et al., 2017 | Adults (university students) | Observational (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | | 101 |
| | Garza et al., 2016 [a] | Adults (19+) | Observational (Acute) | Online | Yes | Adjusting amount | $1000 | 478 |
| | Garza et al., 2019 | Adults | Observational (Acute) | Online | Yes | Adjusting amount | $1000 | 477 |
| | Gearhardt et al., 2017 [a] | Children (7–10) | Observational (Acute) | Laboratory | No | Delay of gratification | Candy | 230 |
| | Groppe and Elsner, 2014 | Children (6–11) | Observational (Acute) | School or home | Yes | Delay of gratification | Candy or toys | 1657 |
| | Howatt et al., 2019 | Adults | Observational (Acute) | Online | Yes | Monetary Choice Questionnaire | | 196 |
| | Hughes et al., 2015 | Children (preschool age) | Experimental (Acute) | Laboratory | Yes (neg. cor.) | Delay of gratification | Candy or snacks | 187 |
| | Kekic et al., 2020 [a] | Adults (18+) | Observational (Acute) | Online | Yes | Adjusting amount | 100 pounds; 50 pounds | 432 |
| | Kelly et al., 2020 | Children and adolescents (8–17) | Experimental (Acute) | Laboratory | No | Adjusting amount | $10 | 205 |
| | Knolle-Veentjer et al., 2008 | Adults | Observational (Acute) | Laboratory | No | Delay of gratification | Candy or snacks | 52 |
| | Leitch et al., 2013 | Adult women | Experimental (Acute) | Laboratory | No | Adjusting amount | 10 pounds | 80 |
| | Lumley et al., 2016 | | | Laboratory | Yes | | Not mentioned | 56 |

(*continued on next page*)

**Table 1** (*continued*)

| Biomarker Criteria | Reference | Study Sample | Study Design | Study Location | Effect | Discounting task used | Magnitude | Sample Size |
|---|---|---|---|---|---|---|---|---|
| | | Adults (university students) | Observational (Acute) | | | Monetary Choice Questionnaire | | |
| | Malesza, 2020 [a] | Adults (20–37) | Observational (Acute) | Laboratory | Yes | Adjusting amount | 300 euros | 305 |
| | Massicotte et al., 2019 | Adults (20–40) | Experimental (Acute) | Laboratory | No | Monetary Choice Questionnaire | | 48 |
| | Mellis et al., 2018a, 2018b | Obese adults | Experimental (Acute) | Online | Yes | Adjusting amount | $100 | 120 |
| | Muñoz Torrecillas et al., 2018 | Adults (university students) | Observational (Acute) | Classroom | Yes | Monetary Choice Questionnaire | | 196 |
| | Peng-Li et al., 2020 | Adults (university students) | Observational (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | | 196 |
| | Pieper and Laugero, 2013 | Children (3–6) | Experimental (Acute) | Laboratory | No | Delay of gratification | Candy, pennies, or prizes | 37 |
| | Rollins et al., 2010 | Adult women | Experimental (Acute) | Laboratory | Yes | Adjusting amount | $10 | 24 |
| | Shuval et al., 2016 | Adults (> = 21) | Observational (Acute) | National survey | Yes | Two questions to calculate discount factor | $12; $15; $18 | 5871 |
| | Temple et al., 2020 | Adolescents (12–14) | Observational (Longitudinal) | Laboratory | No | Adjusting amount (using cards) | $50 | 207 |
| | Yan et al., 2018 | Adults (18–24) | Observational (Acute) | Classroom | No | Monetary Choice Questionnaire | 10,000 yen | 1013 |
| | Zimmerman et al., 2017 | Adults (university students) | Experimental (Acute) | Laboratory | Yes | Adjusting amount | 100 pounds | 70 |
| | Chan, 2017 | Adults | Observational (Longitudinal) | Laboratory and home | Yes | Adjusting amount | $50 | 78 |
| | Epstein et al., 2020 [a] | Adults | Observational (Longitudinal) | Laboratory and home | Yes | Adjusting amount | $100; $1000 | 81 |
| | Guerrero et al., 2019 | Children (8–11) | Observational (Acute) | ABCD study repository | Yes | Hypothetical monetary choice task | $10 | 4524 |
| *Energy expended* | LeComte et al., 2020 | Adults (university students) | Observational (Acute) | Laboratory | Yes | Adjusting amount | $500 | 45 |
| | Leonard et al., 2013 | Adults | Observational (Acute) | Laboratory | Yes | Hypothetical monetary choice task | $150 | 169 |
| | Phillips et al., 2019 | Adults (18–60) | Experimental (Longitudinal) | Laboratory and living environment | Yes | Monetary Choice Questionnaire | | 85 |
| | Sofis et al., 2017 [a] | Adult women | Experimental (Longitudinal) | Outpatient | Yes | Monetary Choice Questionnaire | | 12 |
| **Disease diagnosis** | | | | | | | | |
| | Bickel et al., 2014a, 2014b | Adults (18+) | Observational (Acute) | Online | Yes | Monetary Choice Questionnaire | | 1163 |
| | Bickel et al., 2018 | Adults (18+) | Observational (Acute) | Online | No | Adjusting Amount | $100 and $1000 | 1200 |
| | Bonato and Boland, 1983 | Children (8–11) | Observational (Acute) | Laboratory | Yes | Delay of gratification | candy | 40 |
| | Bongers et al., 2015 | Adults (18–45) | Observational (Acute) | Laboratory | No | Adjusting amount | 1000 euros | 319 |
| | Buono et al., 2015 | Adults (18–27 & 45–55) | Observational (Acute) | Laboratory | Yes | Adjusting amount | $1000 | 38 |
| Distinguishing obese from non-obese: case/control | Call et al., 2017 | Adolescents (13–18) | Observational (Acute) | Laboratory | No | Monetary Choice Questionnaire | | 133 |
| | Dassen et al., 2018 [a] | Adults (18+) | Experimental (Longitudinal) | Laboratory | No | Monetary Choice Questionnaire | | 153 (baseline) |
| | Davis et al., 2010 [a] | Adult women (25–45) | Observational (Acute) | Laboratory | Yes | Adjusting amount | $100 | 209 |
| | DeHart et al., 2020 | Adults (18+) | Observational (Acute) | Online | Yes | Adjusting amount | $100 | 700 |
| | Eisenstein et al., 2015 [a] | Adults | Observational (Acute) | Laboratory | No | Adjusting amount | $500 | 45 |
| | Feda et al., 2015 | Adolescents (13–17) | Observational (Acute) | Laboratory | Yes | Adjusting amount | $10 and $100 | 46 |

(*continued on next page*)

**Table 1** (*continued*)

| Biomarker Criteria | Reference | Study Sample | Study Design | Study Location | Effect | Discounting task used | Magnitude | Sample Size |
|---|---|---|---|---|---|---|---|---|
| | Fields et al., 2011 [a] | Adolescents (13–19) | Observational (Acute) | Laboratory | Yes | Adjusting amount | $10 | 36 |
| | Fields et al., 2013 | Adolescents (14–16) | Observational (Acute) | Laboratory | Yes | Adjusting amount | $10 | 61 |
| | Garza et al., 2016 [a] | Adults (19+) | Observational (Acute) | Online | Yes | Adjusting amount | $1000 | 478 |
| | Gearhardt et al., 2017 [a] | Children (7–10) | Observational (Acute) | Laboratory | No | Delay of gratification | Candy | 230 |
| | Geller et al., 1981 | Children | Observational (Acute) | Laboratory | No | Delay of gratification | Food and toys | 48 |
| | Graham Thomas et al., 2015 | Adults | Observational (Acute) | Online | Yes | Adjusting amount | $1000 | 450 |
| | Hendrickson and Rasmussen, 2017 | Adults | Observational (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | | 348 |
| | Hendrickson and Rasmussen, 2013 | Adults (undergraduates) | Observational (Acute) | Laboratory | No | Adjusting amount | $10 | 304 |
| | Jarmolowicz et al., 2014 | Adults (18–55) | Observational (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | | 100 |
| | Kulendran et al., 2014 | Adolescents (10–17) | Observational (Longitudinal) | Laboratory | Yes | Adjusting amount | $20-$50 | 103 |
| | Kulendran et al., 2016 | Adolescents and adults | Observational (Acute) | Laboratory | Yes | Adjusting amount | $50 | 182 |
| | Lawyer et al., 2015 | Adults (18–30) | Observational (Acute) | Laboratory | Yes | Adjusting amount | $1000 | 296 |
| | Manwaring et al., 2011 [a] | Adult females (18–65) | Observational (Acute) | Laboratory | Yes | Adjusting amount | $100 | 90 |
| | Mole et al., 2015 [a] | Adults (18+) | Observational (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | | 120 |
| | Morys et al., 2018 | Adults (18–35) | Observational (Acute) | Laboratory | Yes | Adjusting amount | Not mentioned | 56 |
| | Myers et al., 2020 | Adults (18–49) | Observational (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | | 56 |
| | Nederkoorn et al., 2006 | Adult females (18–49) | Observational (Acute) | Laboratory | No | Adjusting amount | $1000 | 59 |
| | Price et al., 2016 | Adults (18+) | Observational (Acute) | Laboratory | Yes | Adjusting amount | $100 | 79 |
| | Schiff et al., 2016 | Adults (18–50) | Observational (Acute) | Laboratory | No | Adjusting amount | $40 | 46 |
| | Simmank et al., 2015 | Adults (18–35) | Observational (Acute) | Laboratory | Yes | Adjusting amount | Not mentioned | 52 |
| | Soofi et al., 2019 | Adults (35–65) | Observational (Acute) | National survey | Yes | Five questions to calculate discount factor | | 792 |
| | Steward et al., 2017 | Adult women (18+) | Observational (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | | 160 |
| | Stoklosa et al., 2018 | Adults | Observational (Acute) | National survey | Yes | Two questions to calculate discount factor | | 5871 |
| | Syan et al., 2019 | Adults (22–35) | Observational (Acute) | Laboratory | Yes | Not mentioned | not mentioned | 712 |
| | Verdejo-García et al., 2010 | Adolescents (13–16) | Observational (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | | 61 |
| | Wainwright et al., 2018 | Adults (undergraduates) | Observational (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | | 801 |
| | Weller et al., 2008 | Adults (18–50) | Observational (Acute) | Laboratory | Yes | Adjusting amount | $1000 and $50,000 | 112 |
| | Yeomans et al., 2008 | Adult women | Observational (Acute) | Laboratory | No | Adjusting amount | $10 | 147 |
| | Zimmerman et al., 2018 | Adults | Observational (Acute) | Laboratory | Yes | Adjusting amount | $100 | 66 |
| | Avila et al., 2016 | Adolescents | Observational (Acute) | Laboratory | Yes | Adjusting amount | Not mentioned | 124 |
| Continuous associations of BMI & DD | Bennett and Blissett, 2017 [a] | Children (2–4) | Observational (Acute) | Laboratory | No | Delay of gratification | chocolate buttons | 95 |
| | Borghans and Golsteyn, 2006 | Adults and adolescents (16+) | Observational (Acute) | National survey | Yes | Two questions to calculate discount factor | | 2059 |
| | | Adults | | Laboratory | No | | $100 | 80 |

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**Table 1** (*continued*)

| Biomarker Criteria | Reference | Study Sample | Study Design | Study Location | Effect | Discounting task used | Magnitude | Sample Size |
|---|---|---|---|---|---|---|---|---|
| | Brace and Yeomans, 2016 | | Observational (Acute) | | | Adjusting Amount | | |
| | Bruce et al., 2011 | Children (8–12) | Observational (Longitudinal) | Laboratory | Yes | Delay of gratification | toy | 59 |
| | Chabris et al., 2008 | Adults | Observational (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | | 146 |
| | Dassen et al., 2015 | Adults (18–60) | Observational (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | | 152 |
| | de Oliveira et al., 2016 | Adults | Observational (Longitudinal) | Laboratory | No | Six questions to calculate discount factor | | 486 |
| | Dodd, 2014 | Adults & adolescents (15+) | Obserational (Acute) | National survey | Yes | Single item task | | 1868 |
| | Dogbe and Gil, 2019 | Adults | Observational (Acute) | Laboratory | Yes | Adjusting amount | Not mentioned | 173 |
| | Duckworth et al., 2010 | Adolescents | Observational (Longitudinal) | Laboratory | Yes | Monetary Choice Questionnaire | | 105 |
| | Epstein et al., 2003 | Adult (18+) | Observational (Acute) | Laboratory | No | Monetary Choice Questionnaire | | 78 |
| | Epstein et al., 2014a, 2014b | Adult women (18+) | Observational (Longitudinal) | Online | Yes | Adjusting amount | 10$, $100 | 199 |
| | Garza et al., 2013 | Adults | Observational (Acute) | Online | Yes | Adjusting amount | $1000 | 172 |
| | Groppe and Elsner, 2017 [a] | Children (6–11) | Observational (Longitudinal) | Laboratory | No | Delay of gratification | toys and candy | 1619 |
| | Hendrickson et al., 2015 | Adults (undergraduates) | Observational (Acute) | Laboratory | No | Adjusting amount; Monetary Choice Questionnaire | $10 | 70 |
| | Hovens et al., 2019 | adults (22–35) | Observational (Acute) | National survey | Yes | Adjusting amount | $40,000 | 1027 |
| | Ikeda et al., 2010 | Adults | Observational (Acute) | Online | Yes | Five questions to calculate discount factor | ~$100 | 2987 |
| | Kekic et al., 2020 [a] | Adults (18+) | Observational (Acute) | Online | Yes | Adjusting amount | 100 pounds; 50 pounds | 432 |
| | Lim and Bruce, 2015 | Adults | Observational (Acute) | Online | No | Monetary Choice Questionnaire | | 42 |
| | Lu et al., 2014 | Adolescents | Observational (Acute) | Laboratory | No | Adjusting amount | $100 | 87 |
| | Malesza, 2020 [a] | Adults (20–37) | Observational (Acute) | Laboratory | Yes | Adjusting amount task | 300 euros | 305 |
| | Meyre et al., 2019 | Adults | Observational (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | | 998 |
| | Power et al., 2016 | Children (4–5) | Observational (Acute) | Laboratory | No | Delay of gratification | | 187 |
| | Reimers et al., 2009 | Adults (21–65) | Observational (Acute) | National survey | Yes | Single item task | | 42,863 |
| | Richards et al., 2010 | Adults (18+) | Observational (Acute) | Laboratory | Yes | Adjusting amount | | 82 |
| | Rodriguez et al., 2018 | Adults (18+) | Observational (Acute) | Laboratory | No | Monetary Choice Questionnaire | | 110 |
| | Stojek et al., 2014 | Adults | Observational (Acute) | Laboratory | No | Monetary Choice Questionnaire | | 108 |
| | Thamotharan et al., 2016 | Adolescent women (13–19) | Observational (Acute) | Laboratory | Yes | Adjusting amount | $10 | 60 |
| | VanderBroek-Stice et al., 2017 | Adults | Observational (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | | 181 |
| | Veillard and Vincent, 2020 | Adults (18+) | Observational (Acute) | Online | No | Monetary Choice Questionnaire | | 381 |
| | Wang et al., 2016 | Adults | Observational (Acute) | National survey | Yes | Two questions to calculate discount factor | | 6000 |
| | | | | Laboratory | Yes | | | 159 |

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**Table 1** (*continued*)

| Biomarker Criteria | Reference | Study Sample | Study Design | Study Location | Effect | Discounting task used | Magnitude | Sample Size |
|---|---|---|---|---|---|---|---|---|
| Measuring Disease Severity | Westwater et al., 2019 [a] | Adults and adolescents | Observational (Acute) | | | Monetary Choice Questionnaire | | |
| | Appelhans et al., 2011 [a] | Adult women (18–45) | Experimental (Acute) | Laboratory | No | Adjusting Amount | $100 | 62 |
| | Appelhans et al., 2012 [a] | Adult women (18–45) | Observational (Longitudinal) | Natural environment | No | Adjusting Amount | $100 | 78 |
| | Kishinevsky et al., 2012 [a] | Adult women (19–50) | Observational (Longitudinal) | Laboratory | No | Monetary Choice Questionnaire | | 19 |
| | Manasse et al., 2014 | Adult women (18–70) | Observational (Acute) | Laboratory | No | Adjusting amount | Not mentioned | 80 |
| | Deshpande et al., 2019 | Adults | Observational (Acute) | Laboratory | Yes | Adjusting amount and IDT | $1000 | 53 |
| | Kekic et al., 2014 | Adult Women | Observational (Acute) | Laboratory | No | Adjusting amount | 100 pounds (UK) | 17 |
| Relationship between temporal discounting and biological components of obesity: Neuroimaging | Kishinevsky et al., 2012 [a] | Adult women (19–50) | Observational (Longitudinal) | Laboratory | Yes | Monetary Choice Questionnaire | | 19 |
| | Martin et al., 2015 | Adults | Observational (Acute) | Laboratory | Yes | Adjusting amount | Not mentioned | 19 |
| | Stoeckel et al., 2013 | Adult women | Observational (Acute) | Laboratory | Yes | Adjusting amount | Not mentioned | 19 |
| | van der Laan et al., 2016 | Women | Observational (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | Not mentioned | 20 |
| *Neorochemical functioning* | Westwater et al., 2019 [a] | Adults and adolescents | Observational (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | | 159 |
| | Eisenstein et al., 2015 [a] | Adults | Observational (Acute) | Laboratory | Yes | Adjusting amount | $500 | 45 |
| | Klement et al., 2018 | Men | Experimental (Acute) | Laboratory | No | Monetary Choice Questionnaire | | 40 |
| | Lange and Eggert, 2014 | Adults (university students) | Experimental (Acute) | Laboratory | No | Adjusting amount | 1000 euros | 185 |
| | Sawicki et al., 2019 | Healthy men (18–35) | Experimental (Acute) | Laboratory | No | Adjusting amount | $750/$780 | 100 |
| | Wang and Huangfu, 2017 | Adults (university students; 19–26) | Experimental (Acute) | Laboratory | Yes | Adjusting amount | 182/156,000 yuen | 250 |
| | Wang and Dvorak, 2010 | Adults (university students; 19–51) | Experimental (Acute) | Laboratory | Yes | Adjusting amount | $750 | 65 |
| **Measures of disease progression** | | | | | | | | |
| Temporal discounting as a predictor of weight change | Bjorlie and Fazzino, 2020 | College freshman | Observational (Longitudinal) | Laboratory | No | Monetary Choice Questionnaire | | 80 |
| | Felton et al., 2020 | Adolescents | Observational (Longitudinal) | Laboratory | Yes | Monetary Choice Questionnaire | | 154 |
| | Groppe and Elsner, 2017 [a] | Children (6–11) | Observational (Longitudinal) | Laboratory | No | Delay of gratification | toys and candy | 1619 |
| | Davis et al., 2010 [a] | Adult women (25–45) | Observational (Acute) | Laboratory | Yes | Adjusting amount | $100 | 209 |
| | Epstein et al., 2019 | Adults with Prediabetes | Observational (Longitudinal) | Laboratory | Yes | Adjusting amount | $100 and $1000 | 65 |
| | Epstein et al., 2020 [a] | Adults | Observational (Longitudinal) | Laboratory and home | Yes | Adjusting amount | $100 and $1000 | 81 |
| | Fields et al., 2011 [a] | Adolescents (13–19) | Observational (Acute) | Laboratory | Yes | Adjusting amount | $10 | 36 |
| Relationship to co-morbidities | Manasse et al., 2015a | Women w/ and w/o BED | Observational (Acute) | Laboratory | Yes | Adjusting amount | Not mentioned | 74 |
| | Manasse et al., 2015b | Overweight and Obese Women w/ and w/o Binge Eating | Observational (Acute) | Laboratory | Yes | DDT (adjusting amount) | Not mentioned | 74 |
| | Manwaring et al., 2011 [a] | Adult females (18–65) | Observational (Acute) | Laboratory | Yes | Adjusting amount | $100 | 90 |
| | Mole et al., 2015 [a] | Adults (18+) | Observational (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | | 120 |
| **Predict treatment prognosis/outcomes** | | | | | | | | |
| Temporal discounting as a predictor of | Best et al., 2012 | Children | Experimental (Longitudinal) | Laboratory | Yes | Monetary Choice Questionnaire | | 185 |

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**Table 1** (*continued*)

| Biomarker Criteria | Reference | Study Sample | Study Design | Study Location | Effect | Discounting task used | Magnitude | Sample Size |
|---|---|---|---|---|---|---|---|---|
| obesity treatment outcomes | Manasse et al., 2017 | Adults | Experimental (Longitudinal) | Laboratory | Yes (negative correlation) | Adjusting amount | $1000 | 190 |
| | Dassen et al., 2018 [a] | Adults (18+) | Experimental (Longitudinal) | Laboratory | No | Monetary Choice Questionnaire | | 76 (longitudinal portion) |
| | Manasse et al., 2018 | Adults | Experimental (Longitudinal) | Laboratory | No/Yes | Adjusting amount | $1000 | 189 |
| **Measure treatment effectiveness** | | | | | | | | |
| Temporal discounting is modifiable in overweight/ obese populations | Kao et al., 2019 | Adults | Experimental (Acute) | Laboratory | Yes | Adjusting amount | NT $2000 | 93 |
| | Lewittes and Israel, 1978 | Children | Experimental (Acute) | Laboratory | Yes | Delay of gratification | Marshmallow or pretzel | 48 |
| | Snider et al., 2020 | Adults | Experimental (Acute) | Laboratory | Yes | Brief 5-trial adjusting delay | $100 | 48 |
| | Stein et al., 2017 | Adults | Experimental (Acute) | Online | Yes | Adjusting amount; Brief 5-trial adjusting delay | $100 | 137 |
| | Athamneh et al., 2020 | Adults | Experimental (Acute) | Online | Yes | Monetary Choice Questionnaire | | 255 |
| | Bickel et al., 2020 | Adults | Experimental (Acute) | Laboratory/ outpatient | No | Adjusting amount | $1000 | 67 |
| | Chang et al., 2020 | Adults | Experimental (Acute) | Laboratory | No | Monetary Choice Questionnaire | | 136 |
| | Daniel et al., 2013 | Adult women | Experimental (Acute) | Laboratory | Yes | Adjusting amount | $100 | 26 |
| Modified by Episodic Future Thinking interventions | Daniel et al., 2015 | Children (9–14) | Experimental (Acute) | Laboratory | Yes | Adjusting amount | $50 | 42 |
| | Dassen et al., 2016 | Adult women | Experimental (Acute) | Laboratory | Yes | Monetary Choice Questionnaire | | 95 |
| | Hollis-Hansen et al., 2020 | Adult women & children (2–15) | Experimental (Acute) | Outpatient | No | Adjusting amount | Not mentioned | 43 |
| | Kakoschke et al., 2018 | Adults | Experimental (Longitudinal) | Outpatient | No | Adjusting amount | $100 | 60 |
| | Mansouri et al., 2020 | Adults | Experimental (Acute) | Outpatient | No | Brief 5-trial adjusting delay | $100 | 33 |
| | Stein et al., 2020 | Adults | Experimental (Acute) | Laboratory | No | Adjusting amount | $1000 | 78 |
| | Sze et al., 2017a, 2017b | Adults | Experimental (Acute) | Online | Yes | Monetary Choice Questionnaire | | 204 |
| | Kulendran et al., 2017 | Adults | Experimental (Longitudinal) | Outpatient | No | Adjusting amount | L10 (pounds) | 45 |
| Modified by weight-loss interventions | Sofis et al., 2017 [a] | Adult women | Experimental (Longitudinal) | Outpatient | Yes | Monetary Choice Questionnaire | | 12 |
| | Takada et al., 2011 | Adults | Experimental (Longitudinal) | Outpatient | Yes | Two questions to calculate discount factor | $10,000 yen | 118 |

Note; For the purpose of this review, we reported the final sample included in each study.
Note; Experimental refers to studies that employ a manipulation. Observational refers to studies that observe behavior and do not employ a manipulation. Acute refers to studies with a single time point. Longitudinal refers to studies with multiple time points.
[a] This paper contains more than one study or refers to more than one obesity domain and was described in more than one subsection of this manuscript.

and self-reported questionnaire-based measures of food consumption. Specifically, steep TD is associated with disinhibited eating, compulsive overeating, food addiction as measured by the Yale Food Addiction Scale, as well as other measures of eating disorder psychopathology in adults, some of whom self-reported an eating disorder (Kekic et al., 2020; Lumley et al., 2016; Peng-Li et al., 2020). A recent study also revealed that steep TD is associated with a narrowing attentional focus in response to dessert cues (as measured by the Attentional Scope Task), which the authors suggest may contribute to a heightened drive to consume foods, especially those high in fat and sugar (Fields et al., 2017). Other studies, however, have found no relationship between TD and self-reported measures of uncontrolled eating, as assessed by the Three Factor Eating Questionnaire (Leitch et al., 2013). Additionally a recent study found no significant differences in TD between binge-eaters versus non-binge-eaters, as measured by the Binge Eating Scale (Yan et al., 2018).

Others have approached the subject using laboratory-based eating studies. One laboratory-based study in overweight/obese women using an eating in the absence of hunger protocol found that high levels of palatable food intake were predicted by the interaction of TD and hedonic hunger. Higher hedonic hunger levels were only associated with increased food consumption in individuals who were also steep discounters (Appelhans et al., 2011). Similar studies have shown support for the relationship between TD, hedonic hunger, and food consumption (Ely et al., 2015), and others have found that the relative reinforcing value (RRV) of food predicted *ad libitum* eating, but TD moderated this

effect; the steeper the TD rate, the greater the total energy intake (Rollins et al., 2010). Some work has revealed no relationship between TD and food consumption of either bland foods or highly-palatable foods (Massicotte et al., 2019), but suggest that examining other executive functions (such as inhibition and flexibility) may add important information regarding the regulation of food intake (Knolle-Veentjer et al., 2008; Massicotte et al., 2019; Pieper and Laugero, 2013).

Finally, some studies have measured food consumption in the natural environment, a task that has proven challenging because of the inaccuracy of existing self-report measures (Johnson, 2002). One study in overweight and obese women investigated TD's relationship to daily food consumption for seven days using a weighed food record diary (Appelhans et al., 2012). Steeper TD was related to a greater caloric consumption of both away-from-home or ready-to-eat foods. Moreover, the increased caloric consumption was driven by the caloric density of the food (rather than the weight), suggesting that the foods chosen were highly processed and highly palatable (Appelhans et al., 2012). This suggests that increased TD may be associated with a greater sensitivity to hyperpalatable foods (i.e., foods high in fat and/or sugar); in fact, neuroimaging studies have shown that obese compared to lean individuals demonstrate increased activation of reward regions of the brain in response to high-calorie food pictures or anticipation of the consumption of high-calorie foods (Del Parigi et al., 2003; Murdaugh et al., 2012; Ng et al., 2011; Samara et al., 2018; Volkow et al., 2008).

Other research examined the relationship between TD and food consumption in individuals with low SES. For example, heightened TD in individuals with low income levels predicts food insecurity (Epstein et al., 2014b), which is associated with a 32 % increased odds of being obese (Pan et al., 2012). Additionally, TD mediates the effects between certainty of meal times and portion size selection (Zimmerman et al., 2017). That is, in conditions of uncertain meal times (i.e., unknown intermeal intervals), often present in individuals with low SES, individuals with steep TD choose smaller portion sizes than those with shallow TD. The authors suggest that TD may be especially influential in "chaotic" eating environments, where meal times are uncertain or irregular. Therefore, planned or consistent meal times may help to regulate food consumption in those individuals with heightened TD. Interestingly, research from our group has shown that negative income shock, a situation that occurs frequently in individuals with low SES, both increases TD as well as demand for fast food in obese individuals (Mellis et al., 2018a), which may be one reason why the increased purchasing and consumption of fast foods is heightened in communities with low SES. Further, a longitudinal study using data from the US Bureau of Labor Statistics that tracked 12,686 individuals over 21 years found that higher rates of TD (assessed via a two item task; see Box 1 for description and limitations of this task variant) were associated with increases in BMI over time, with this relationship being strongest in counties with the lowest food prices (Courtemanche et al., 2015). Lending additional support, heightened TD rates have been observed in communities with heightened concentrations of fast food restaurants, which are often low SES communities (DeVoe et al., 2013).

Studies using the delay of gratification, primarily in children and adolescents, have shown less support for the interconnected relationship to food consumption. That is, some studies have found a positive relationship between delay of gratification and food intake (Bennett and Blissett, 2019), whereas others have shown no relationship (Bennett and Blissett, 2017; Pieper and Laugero, 2013) or a negative correlation (Hughes et al., 2015). One study in children and adolescents (8−17 years of age) found no relationship between delay of gratification and food consumption in a laboratory-based buffet where participants were instructed to "Let yourself go and eat as much as you want" (Kelly et al., 2020). Additionally, no association was found between TD and food sensitization (as measured by RRV) after two weeks of high energy density food consumption in a group of adolescents (Temple et al., 2020). However, a recent cross-sectional study in low income children found a significant positive association between delay of gratification and RRV; this association was only found in girls (not boys) (Gearhardt et al., 2017). Finally, difficulty to delay gratification was associated with parental ratings of emotional overeating in children (6−11 years of age) (Groppe and Elsner, 2014). Only one study utilized a delay of gratification task in schizophrenic adults and healthy controls, finding no association with self-reported measures of uncontrolled eating (Knolle-Veentjer et al., 2008).

Collectively, this body of research demonstrates that TD is associated with overconsumption of foods, especially unhealthy, high energy density foods, with individuals in low SES standing being especially vulnerable to this effect. However, studies that utilize the delay of gratification task (prominently those in children and adolescence) show less of a relationship to food consumption, which suggests either a developmental effect (i.e., the relationship only emerges in adulthood) or a methodological one (i.e., TD is a more sensitive measure than delay of gratification).

#### 3.2.2. *Energy expenditure*

Lack of physical activity and sedentary behavior are other maladaptive behaviors impacting overweight and obese outcomes. Limited work has been done to investigate the relationship between TD and physical activity in obese individuals. Cross-sectional studies have revealed a clear association between BMI and physical activity behaviors, showing negative correlations to exercise and positive correlations to sedentary behaviors (e.g., screen time) (Banks et al., 2011; Dwyer--Lindgren et al., 2013; Melby et al., 2019). Moreover, a meta-analysis analyzing 52 studies found that steeper discounting is predictive of decreased exercise behaviors, albeit with a small effect size (Sweeney and Culcea, 2017), and newer cross-sectional work has found an association between steep TD and decreased weekly exercise sessions (LeComte et al., 2020). Our laboratory has also shown that steep TD is associated with lower levels of physical activity in prediabetic adults as measured by acceleromoetry data captured over one week (Epstein et al., 2020). Additionally, one community-based study in a low-income, urban, African American neighborhood found that steep TD predicted being in a less advanced stage of physical activity, that is, a precontemplation or preparation phase rather than an action or maintenance phase (Leonard et al., 2013).

Few studies have taken an interventional approach to examine how physical activity engagement impacts TD in overweight or obese individuals. One investigation on the effects of contingency management on physical activity among inactive, overweight adults found that heightened rates of TD predicted exercise non-adherence (Phillips et al., 2019). No studies to date have examined the acute effects of exercise on TD; however, preliminary evidence suggests that long-term exercise significantly decreases TD in individuals with weight-related issues (Sofis et al., 2017). Future research is needed to investigate the interaction between BMI, TD, and physical activity. Programs that target TD to increase physical activity need to consider a range of activities, includingexercise and lifestyle activities such as housework, yard work, walking up the steps, and less screen time. Considering alternatives to traditional aerobic exercise may be especially important in overweight and obese populations who find this type of movement physically difficult or inherently aversive (Dalle Grave et al., 2011). Of relevance, a recent study found that physical activities requiring greater amounts of energy expenditure (e.g., walking versus sitting) are discounted more steeply and thus may require greater incentives for participation (Hsu and Vlaev, 2014).

Poor sleep patterns are also considered here as a maladaptive behavior because they: 1) contribute to TDEE; 2) are an important regulator of neuroendocrine function and glucose metabolism; and 3) have been linked to obesity (e.g., insufficient sleep; sleep deprivation) (Beccuti and Pannain, 2011; Markwald et al., 2013). A large cross-sectional study in 4524 children between the ages of 8 and 11 found that steeper discounting rates were associated with lower adherence to the Canadian 24-Hour Movement Guidelines for Children and

Youth, which included recommendations for daily sleep time, recreational screen time, and physical activity (Guerrero et al., 2019). Additionally, one study using actigraph measures for 7 days found that TD moderated the relationship between various sleep measures and BMI (Chan, 2017). Namely, irregular sleep patterns (i.e., circadian desynchronization) were associated with heightened BMI, and individuals with steeper discounting were more vulnerable to this effect (Chan, 2017).

Collectively, this work suggests that high TD is associated with decreased physical activity and impaired sleep, which along with increased food consumption, contributes to heightened BMI and overweight or obese outcomes. More interventional studies are needed to examine the impact of increasing physical activity on TD.

## 4. Disease diagnosis

When an individual has progressed from being at risk to acquiring a disease, the second measure of a biomarker's utility is to detect the presence of such a disease. This section first considers the evidence that TD can distinguish between individuals with and without obesity. Next, we examine if TD can predict the magnitude of obesity (i.e., disease severity). Lastly, we consider the evidence for associations between TD and biological components of obesity, including neuroanatomical and cellular/molecular functioning.

### *4.1. Distinguishing obese from non-obese*

To qualify as a behavioral marker, TD should sufficiently differentiate individuals with and without obesity. Research comparing TD rates among obese individuals and healthy controls has repeatedly shown that obese individuals have a comparatively higher average discount rate. The first published investigation of greater TD compared rates between obese women and demographically matched healthy weight women (Weller et al., 2008). Across two magnitudes ($1000, $50,000), the obese group discounted delayed monetary rewards significantly more than controls. Specifically, the delayed hypothetical $1000 lost 50 % of its subjective value at a 6-month delay among healthy weight individuals, while among obese individuals, the same amount lost 50 % of its value in approximately 3 months. More striking differences were noticed in the $50,000 hypothetical task, where for healthy weight individuals, a 50 % loss of value was seen at 36 months, while for obese individuals, this same percentage loss was seen at 3 months. The ability of TD to distinguish individuals with obesity from healthy weight individuals has been replicated in six subsequent studies of adolescents (Feda et al., 2015; Fields et al., 2013, 2011; Kulendran et al., 2016, 2014; Verdejo-García et al., 2010) and 19 studies of adults (Bickel et al., 2014a; Buono et al., 2015; Davis et al., 2010; DeHart et al., 2020; Garza et al., 2016; Graham Thomas et al., 2015; Hendrickson and Rasmussen, 2017; Jarmolowicz et al., 2014; Lawyer et al., 2015; Mole et al., 2015; Morys et al., 2018; Myers et al., 2020; Price et al., 2016; Simmank et al., 2015; Soofi et al., 2019; Steward et al., 2017; Stoklosa et al., 2018; Syan et al., 2019; Zimmerman et al., 2018). One study in adult undergraduate students showed that obese individuals had significantly greater TD rates when compared to underweight individuals, but not to healthy weight individuals (Wainwright et al., 2018). Additionally, in another study obese individuals with binge eating disorder (BED) had significantly greater rates when compared to a group of obese without BED and healthy controls, but the obese only group was not significantly different than the healthy controls (Manwaring et al., 2011).

In contrast, ten case-control studies have demonstrated no significant relationship between monetary discounting and weight status (Bickel et al., 2018; Bongers et al., 2015; Call et al., 2017; Dassen et al., 2018; Eisenstein et al., 2015; Hendrickson and Rasmussen, 2013; Kulendran et al., 2016; Nederkoorn et al., 2006; Schiff et al., 2016; Yeomans et al., 2008). However, the majority of these studies include one or more methodological considerations that may limit the generalizability of these findings, including: 1) the use of small amounts of money in discounting tasks, which may not elicit group differences (Hendrickson and Rasmussen, 2013; Schiff et al., 2016; Yeomans et al., 2008); 2) sampling from treatment-seeking individuals, who may possess greater self control and future valuation than the obese population at large (Bickel et al., 2018; Bongers et al., 2015; Call et al., 2017; Dassen et al., 2018; Kulendran et al., 2016; Schiff et al., 2016); and 3) groups differing significantly by education and/or income status (Bickel et al., 2018; Bongers et al., 2015). While several studies showing a positive association between TD and obesity also included potential limitations such as groups differing by education and/or income (Davis et al., 2010; Fields et al., 2013; Graham Thomas et al., 2015; Morys et al., 2018; Myers et al., 2020; Stoklosa et al., 2018) and inclusion of treatment seeking individuals (Fields et al., 2011; Steward et al., 2017), a smaller proportion of the studies demonstrating a positive association presented these potential limitations (8/28) compared to the studies showing no association (8/10).

Investigations of continuous associations between TD and body mass index have demonstrated similar findings. Fifteen studies of adults (Borghans and Golsteyn, 2006; Chabris et al., 2008; Dassen et al., 2015; Dogbe and Gil, 2019; Epstein et al., 2014a; Garza et al., 2013; Hovens et al., 2019; Ikeda et al., 2010; Kekic et al., 2020; Malesza, 2020; Meyre et al., 2019; Reimers et al., 2009; Richards et al., 2010; VanderBroek-Stice et al., 2017; Wang et al., 2016), three of adolescents (Avila et al., 2016; Duckworth et al., 2010; Thamotharan et al., 2016) and two studies of adolescents and adults (Dodd, 2014; Westwater et al., 2019) have found a significant positive relationship between discounting rate and BMI. In contrast, eight studies in adults demonstrated no significant relationship between discounting rate and BMI (Brace and Yeomans, 2016; Epstein et al., 2003; Hendrickson et al., 2015; Lim and Bruce, 2015; Power et al., 2016; Rodriguez et al., 2018; Stojek et al., 2014; Veillard and Vincent, 2020). Additionally, a study of chinese adolescents found a negative association between discounting rate and BMI for both males and females, while a positive association between discounting rate and percent body fat was observed for females (Lu et al., 2014). Again, methodological considerations potentially limit the interpretation of these findings including: 1) the use of small amounts of money in discounting tasks (Hendrickson et al., 2015); 2) a restricted range of BMI in the sample (Brace and Yeomans, 2016; Epstein et al., 2003; Rodriguez et al., 2018); and 3) inclusion of individuals seeking treatment or interested in weight loss (Lim and Bruce, 2015; Stojek et al., 2014; Veillard and Vincent, 2020). While a small number of continuous studies demonstrating a positive association between TD and BMI also included the potential limitation of small amounts of money in the discounting task (Epstein et al., 2014a; Thamotharan et al., 2016), the overall proportion of studies demonstrating positive association between TD and BMI is lower (2/20) compared to studies showing no association (7/9).

An additional avenue of investigation has been to examine children's ability to delay gratification in relation to weight status. These studies have demonstrated mixed results. For case-control, one study found that ability to delay gratification for an edible reward was significantly different between obese and healthy weight children (Bonato and Boland, 1983). In contrast, two studies showed that delay was not associated with weight status but was associated with weight relevant factors. Geller et al. (1981) compared ability to delay gratification for a food reward in obese and non obese children and showed that while there was no difference in delay, the obese children ate the reward faster. Additionally, Gearhardt et al. (2017) showed that while delay did not predict weight status, it did predict higher relative reinforcing value of food in girls. Continuous associations of BMI and ability to delay gratification have shown similar mixed findings. One study showed that children with higher bmi were less likely to delay receiving a non-edible reward (Bruce et al., 2011). While two studies involving edible rewards (Bennett and Blissett, 2017; Power et al., 2016) and one of non-edible rewards (Groppe and Elsner, 2017) demonstrated no association between ability to delay gratification and weight status. Gearhardt et al.

(2017) suggest that at the early childhood developmental stage, ability to delay gratification for food may reflect differences in emotional regulation, as opposed to executive function.

In sum, investigations have demonstrated a robust association of higher TD rates with obesity in case-control and continuous study designs, with a majority of case-control studies (28 out of 38) and continuous studies (20 out of 29) showing a positive effect. Additionally, we have outlined methodological considerations that may limit the interpretation of non-significant results. Studies investigating ability to delay gratification in children, a similar construct to TD, have shown mixed associations with weight status. However, this should be interpreted cautiously, as differences in developmental state may limit direct comparison to TD. Overall, considerable methodological variation exists across investigations of weight status and TD and the development of best practices for study design could help to clarify these discrepancies.

### 4.2. Measuring disease severity

For individuals who already present with a disease diagnosis, a biomarker's potential utility is to measure disease severity. Four studies have examined the relationship between TD and BMI in overweight/obese and obese-only samples. Appelhans and colleagues examined overweight/obese women in two separate studies and found no significant relationship between TD and BMI (Appelhans et al., 2011, 2012). Kishinevsky et al. examined obese women and found no significant relationship between TD and BMI (Kishinevsky et al., 2012). Lastly, Manasse et al. examined overweight/obese women with and without loss-of-control eating and found no signficant relationship between TD and BMI (Manasse et al., 2014). These results suggest that in already obese individuals, TD is not a predictor of disease severity. However, all four studies examined women-only samples and three out of four studies included restricted age ranges (Appelhans et al., 2012, 18−45 in 2011; and 19−50 in Kishinevsky et al., 2012). Further investigations in male and mixed-gender samples across a greater age range will be necessary to determine these findings' generalizability.

### 4.3. Relationship between temporal discounting and biological components of obesity

Here we explore the relationship between TD and biological alterations associated with obesity. We first discuss neuroimaging studies of brain structure and function using magnetic resonance imaging (MRI) and functional MRI (fMRI), then discuss the literature on biological alterations and its relationship to TD in obese populations. We acknowledge the potential limitations of fMRI measures outlined in a recent meta-analysis by Elliott et al. (2020), including poor reliability and test-retest reliability.

#### 4.3.1. Neuroimaging and neuromodulation

Investigations of obesity and TD have utilized both MRI and fMRI, allowing researchers to examine brain activity while individuals are making decisions. The examination of TD in neuroimaging research compares brain maps between decisions, appropriately named "hard" versus "easy" (McClure et al., 2007, 2004). "Hard" trials are defined as trials where the subjective value is similar between the immediately available and delayed choice. "Easy" trials, on the other hand, have larger differences in the subjective value between choices available immediately and after a delay.

Examinations of TD and addiction using both MRI and fMRI, and primarily the examination of "hard" versus "easy" trials, have led to the development of the competing neurobehavioral decision system (CNDS) theory (McClure et al., 2004). The CNDS theory proposes that individuals make choices based on the interaction of two decision systems in the brain, the executive and the impulsive, and dysregulation between these systems can cause pathology, such as addiction (Bickel et al., 2011, 2007; McClure and Bickel, 2014). The impulsive system, composed of the limbic (e.g., amygdala, striatum) and paralimbic (e.g., insula, nucleus accumbens) regions of the brain, is associated with the valuation of immediate reinforcers (e.g., food), and responds to emotionally charged stimuli (e.g., threatening or fearful situations) (Bickel et al., 2016, 2013, 2011). The executive system, composed of the parietal lobes and areas of the prefrontal cortex, is involved in future thought, prospection, and the valuation of temporally extended reinforcers (e.g., health). The executive system is also responsible for remembering recent events and modifying plans as time passes (Bickel et al., 2016, 2013, 2011). The CNDS theory also serves as a framework to understand differences in obese individuals' neural activity during decision-making processes (Price et al., 2016). Recent reviews have described the relationship between obesity and the prefrontal cortex (PFC). Gluck et al. (2017) reported that obese individuals have lower excitation levels in the executive system (i.e., left dorsolateral PFC) than lean controls. Lowe et al. (2019) reviewed the relationship between the PFC and obesity and highlighted a potential reciprocal relationship between them (i.e., changes in the PFC may lead to alterations in reward properties from food and ultimately overconsumption; see Lowe et al., 2019).

Lavagnino et al. (2016) reviewed neuroimaging studies of obesity and TD (along with tasks that measure inhibitory control). They reported that, congruent to other results, obese individuals had both greater TD and impaired inhibitory control (i.e., impairment of the executive system) compared to non-obese controls. The study also indicated that lower activation of the executive system (i.e., PFC) affects both TD and BMI. Stoeckel et al. (2013) evaluated TD rates in obese women using fMRI, but compared areas of activation between "hard" and "easy" trial difficulties. Consistent with the results reported by Lavagnino et al. (2016); Stoeckel et al. (2013) demonstrated that greater rates of TD were associated with smaller changes in activation of executive function brain regions between "hard" and "easy" trials. That is, individuals who did not experience as much activation in the executive region between "easy" and "hard" trials showed high rates of TD (i.e., they were less willing to wait for a reward).

Kishinevsky et al. (2012) used fMRI to investigate brain region activation in obese women during "hard" and "easy" task trials. Congruent with previous findings, Kishinevsky et al. reported that "hard" trials on the TD task corresponded to activation of regions associated with the executive function system (i.e., middle and inferior frontal gyri and medial PFC). Interestingly, Kishinevsky et al. reported that decreased activation in these executive function areas predicted greater weight gain rates over the 1.3–2.9 years of follow up. These results suggest that executive function areas, such as the PFC, are related to obesity, weight gain, and TD.

One fMRI study has examined the relationship between obesity, TD, and quality of sleep. Martin et al. (2015) reported that for all participants a significant percent signal change was observed when comparing the selection of the smaller, immediately available reward to the baseline condition of viewing a fixation cross, regardless of the quality of sleep. The significant percent signal change was observed in regions associated with both the executive system (i.e., middle, medial and inferior frontal gyri) and the impulsive system (i.e., insula, lentiform nucleus/medial globus pallidus, and cingulate). Furthermore, when making impulsive decisions, poor quality sleepers had lower brain activation in areas associated with the executive system (i.e., right inferior and right middle frontal gyri) and the impulsive system (i.e., bilateral insula) than the good quality sleepers. Note in other studies that sleep deprivation has been reported to be associated with effort discounting, but not TD (Libedinsky et al., 2013).

One fMRI study examined the relationship between individuals with obesity, prediabetes, and TD. Deshpande et al. (2019) compared hard versus easy trials in the TD task, as well as immediate available versus immediate unavailable. Similar to results mentioned above, "hard" trials had increased activation in areas of the executive system (medial frontal, bilateral superior frontal, middle frontal gyrus, and bilateral inferior parietal lobules) compared to "easy" trials. "Easy" trials, on the other

hand, resulted in increased activation of the impulsive system (right insula and bilateral middle temporal gyrus).

Another fMRI study conducted in weight-concerned women examined the relationship between TD and brain activity when choosing between high and low energy snacks. Van der Laan et al. (2016) reported that TD rates were positively correlated with activation in the bilateral striatum (an area of the impulsive system); women with higher TD had more activation in this area in high energy food choices compared to low energy food choices.

An MRI study conducted by Westwater et al. (2019) examined the relationship between TD, cortical thickness, BMI and adiposity in healthy adolescents. The study reported that although adiposity and TD rates were unrelated, both higher adiposity and higher TD rates were related to lower left triangular inferior frontal gyrus thickness (a region involved in the executive system).

In addition to neuroimaging studies examining brain structure and function, one study examined the effects of transcranial direct current stimulation (tDCS) of the PFC on food craving and TD in women of healthy and overweight BMIs. While Kekic et al. (2014) did not report changes in TD after sham or active tDCS like others have reported in non-obese populations (Figner et al., 2010), they reported that individuals who received active tDCS had sharper decreases in the Food Challenge Task (FCT), used to assess food cravings, than the individuals who received sham tDCS when including TD rate as a covariate. These results suggest that individuals who are less impulsive (willing to wait for temporally extended rewards) are more susceptible to the anti-craving effects of tDCS on the PFC (Kekic et al., 2014).

#### 4.3.2. *Neurochemical functioning*

Other research has examined neurochemical alterations underlying individual differences in TD in obesity. Investigations have primarily focused on dopamine, a neurotransmitter produced in the ventral tegmental area and substantia nigra pars compacta and released in the striatum, nucleus accumbens, and regions of the prefrontal cortex. Dopamine is involved in reward and motivation, and dysregulation in this system has been found to be a prominent biomarker in individuals with substance use disorders (Volkow et al., 2016, 2009, 2007). Recently, obesity has been conceptualized as a food addiction by some investigators (Ferrario, 2017; Lerma-Cabrera et al., 2016). Supporting evidence indicates that similar alterations in the dopaminergic system observed in addiction are seen in individuals with obesity (Blumenthal and Gold, 2010; Schulte et al., 2015; Volkow et al., 2017; Wang et al., 2001). Specifically, positron emission tomography was utilized to examine the relationship between striatal D2 receptor binding and TD in obese and non-obese individuals (Eisenstein et al., 2015). Steeper TD was related to lower ß-cell function in the total sample and decreased insulin sensitivity and heightened striatal D2 receptor binding in obese individuals (Eisenstein et al., 2015). Interestingly, a recent meta analytic study found no significant association between D2 receptor availability and TD in healthy individuals, but significant positive associations among individuals with obesity (Castrellon et al., 2019). That is, steeper TD is associated with heightened dopamine D2 receptor expression in obese but not healthy weight individuals (Castrellon et al., 2019). Similarly, rodent studies have shown that chronic exposure to a high-fat, high-sugar diet induces alterations in the dopamine D2 receptor system (Narayanaswami et al., 2013; Robertson and Rasmussen, 2017). The pharmacological blockade of the dopamine system with haloperidol (a D2 receptor antagonist) also leads to increased TD in rats fed an obesity-inducing diet (Boomhower and Rasmussen, 2014; Robertson and Rasmussen, 2017). Collectively, this work shows that dopamine pathology (e.g., lower dopamine levels and higher receptor density) in obese individuals may play a role in heightened TD.

Another area of inquiry has focused on the association between TD and blood glucose levels. Studies have shown that acute ingestion of glucose (i.e., sugar water) in fasting individuals significantly decreases TD, with a significant negative association seen between blood glucose level and TD (Wang and Dvorak, 2010; Wang and Huangfu, 2017). The greater the rise in blood glucose, and the greater the decrease in hunger, the greater the effect on decreasing TD. Consumption of zero-calorie artificial sweeteners that do not increase blood glucose level either did not affect (Wang and Huangfu, 2017) or significantly increased TD (Wang and Dvorak, 2010). Other studies, using sugar sensing (oral mouth rinse), sugar ingestion, or consumption of a normal meal (breakfast) have failed to show this effect (Lange and Eggert, 2014; Sawicki et al., 2019). The only study investigating this relationship in individuals with obesity utilized a glucose clamp test, the gold standard to increase blood sugar without the confounding effect of the gustatory component of sweet tastes (Klement et al., 2018). Klement et al. (2018) found that increasing blood glucose did not alter TD in either lean or obese men, concluding that a low energy body state does not impact TD and that other mechanisms may be at play. As obese individuals report higher levels of hedonic hunger or having a heightened reward response to the taste and consumption of food, the neural mechanisms supporting these processes and their relationship to TD will be an interesting area of future inquiry.

Finally, a hypothesis-based paper on the neuroeconomic theory of obesity suggested that various neurochemicals involved in obesity may regulate TD and be important parameters to consider in association with TD (Takahashi, 2010). For example, gastrointestinal hormones such as ghrelin, leptin, cholecystokinin, glucagon-like peptide-1 (GLP-1), and peptide YY regulate the gut-brain axis, control food intake, and are important regulators of obesity (Adamska et al., 2014; Perry and Wang, 2012; Steinert et al., 2017). In fact, new pharmacotherapies for obesity, such as Liraglutide (Saxenda), target GLP-1 receptors (GLP-1 agonists) and have been shown to promote weight loss in patients with or without Type 2 diabetes (Crane and McGowan, 2016; Rajeev and Wilding, 2016). Additionally, serotonin and norepinephrine regulate metabolism and have been implicated in overweight/obese outcomes as serotonin-norepinephrine reuptake inhibitors (SNRIs) help decrease food intake and have been utilized for obesity treatment (Kim et al., 2013; Luque and Rey, 1999; Yabut et al., 2019). Finally, stress hormone production (e.g., cortisol; catecholamines) regulates dietary preference, food consumption, and adiposity distribution and has been shown to be dysregulated in obesity (Kyrou and Tsigos, 2009; Scott et al., 2012; Tomiyama, 2019; Torres and Nowson, 2007). Future work will explicitly need to examine the relationship between TD and each of these candidate molecular markers in obesity.

Collectively, this work demonstrates that increased TD in obese individuals may be due to functional impairments in regions of the CNDS including those involved in both the executive and impulsive systems. In addition, alterations in dopamine dynamics, glucose metabolism, and other neuromodulators involved in obesity (e.g., serotonin, norepinephrine, gastrointestinal hormones, cortisol) may be a driver of increased rates of TD. Future animal and human studies are needed to determine the exact biological changes (both in brain structure and function) that underlie TD changes in obesity.

## 5. Measures of disease progression

The third function of a biomarker for obesity is to effectively identify individuals at risk for disease progression (i.e., weight gain) and/or at risk for complications from comorbidities. Here we review the evidence that TD can effectively measure disease progression of obesity. First, we review studies examining TD's ability to predict weight gain. Second, we examine evidence of differences in TD among obese individuals with and without comorbidities, such as binge eating disorder (BED).

### 5.1. *Temporal discounting as a predictor of weight change*

Pertinent to this discussion is TD's ability to predict weight change in an individual over time. Strong empirical support for this predictive ability requires measurements of TD or delay of gratification and weight

(across at least two points in time). To our knowledge, only two studies have longitudinally examined the ability of TD to predict weight change (Bjorlie and Fazzino, 2020; Felton et al., 2020).

Felton et al. (2020) examined TD in relation to weight status during adolescence. Individuals aged 11–15 years old at the beginning of the study completed yearly assessments over a six-year period, allowing an analysis of TD's developmental trajectory. Findings suggested a significant relationship between TD's trajectory and changes in BMI over time, with adolescents who experienced increases in TD rates more likely to experience abrupt increases in BMI.

Bjorlie and Fazzino (2020) examined whether TD at the beginning of the freshman year predicted weight gain across the academic year. Results suggested that TD was not significantly associated with weight at follow-up when accounting for baseline weight and height. This study possessed several limitations. Notably, only 22 out of 80 participants gained weight (4.60 kg, SD = 1.80), reducing the potential predictive ability of TD. Additionally, this study over-sampled participants with risky drinking patterns which could be a potential confound with higher TD rates.

Additionally, one study longitudinally examined the ability of delay of gratification to predict weight change in children. Groppe and Elsner (2017) investigated longitudinal associations between delay of gratification and BMI in children aged 7−11 years old. Delay of gratification and BMI were obtained at two time-points one year apart. No significant association between delay of gratification and change in BMI was detected. However, change in BMI was limited ($p = .90$), and therefore there was not much variance to be explained by a predictor. Although the study detected associations between other executive function measures and BMI, the longitudinal effects were small.

In summary, three studies have investigated the relationship between TD or delay of gratification and weight change over time. One study (Felton et al., 2020) used baseline and follow up measurement of TD/weight, and showed a positive significant relationship between change in TD and weight over time, while two other studies examined TD (Bjorlie and Fazzino, 2020) or delay of gratification (Groppe and Elsner, 2017) at baseline and showed no significant relationship with weight gain. The small number of investigations prevents any definitive statement regarding TD or delay of gratification's ability to predict weight change over time. The field would benefit from additional longitudinal studies to further examine the ability of TD to predict weight change.

### 5.2. Relationship to co-morbidities

Obesity related comorbidities are an important consideration when validating a potential biomarker of obesity. Comorbidities including cardiovascular disease and diabetes can decrease quality of life and increase mortality for individuals with obesity (Abdelaal et al., 2017). TD has been examined in obese individuals with maladaptive health behaviors, such as smoking, and comorbid diagnoses, including pre-diabetes and eating disorders.

One study has examined the relationship between TD, obesity and smoking in adolescents and reported that obese adolescent smokers have higher rates of TD than healthy weight adolescent smokers (Fields et al., 2011). Two studies examined the relationship between TD rate, BMI, and HbA1c in individuals with pre-diabetes. Epstein et al. (2019) examined the association between changes in BMI, HbA1c, and TD rate in individuals with pre-diabetes over one year. The results indicated that changes in HbA1c were significantly related to both changes in BMI and TD rate. The second study by Epstein et al. (2020) examined the relationship between TD, HbA1c, medication adherence, diet quality, and exercise among individuals with pre-diabetes who were also prescribed medication for comorbidities related to pre-diabetes and obesity (i.e., hypertension and/or lipidemia; Nguyen et al., 2008). TD rates for both $100 and $1000 were related to BMI and adherence for hypertension and/or dyslipidemia medications, where individuals with higher BMI and lower medication adherence had higher rates of TD. Additionally, TD rates for $1000 were related to HbA1c and physical activity; individuals with higher HbA1c and lower physical activities reported higher rates of TD.

Other obesity-related comorbidities include eating disorders such as bulimia nervosa (BN) and binge eating disorder (BED). A recent systematic review reported that obesity, BN, and BED are associated with increased rates of TD (McClelland et al., 2016). Five studies have examined TD in individuals with BED and obesity. First, Davis et al. (2010) reported that both obese individuals with comorbid BED and individuals with BED alone reported higher discounting than normal weight controls. Interestingly, the group differences were not significant when education was added to the model (Davis et al., 2010). Second, a study by Manwaring et al. (2011) reported that obese women with comorbid BED discounted more than obese women without BED, and controls. Third, consistent with the previously mentioned studies, Manasse et al. (2015b) reported that overweight and obese women with BED discounted more than overweight and obese women (without or with subthreshold BED). Fourth, Mole et al. (2015) examined TD in obese individuals with and without BED and abstinent alcohol-dependent individuals. Obese individuals with BED, obese individuals without BED, and alcohol-abstinent individuals had higher TD rates than healthy controls (Mole et al., 2015). Interestingly, BMI was not correlated with k-value in obese individuals with or without BED in this sample (Mole et al., 2015). Fifth, Manasse et al. (2015a) report that in treatment seeking overweight and obese women, those with binge eating episodes had higher TD rates and higher hedonic hunger than individuals without binge eating episodes. Together, these results of the significant relationship between TD, obesity and obesity-related comorbidities suggest that having both obesity and obesity-related comorbidities is associated with more extreme discounting (less valuation of the future) than having obesity alone.

## 6. Predict treatment prognosis/outcomes

A fourth utility of a behavioral marker is the ability to indicate treatment prognosis/outcomes. Although the standards for successful treatment of obesity have evolved with our understanding of the disease process, weight loss has been the traditional outcome measure of effectiveness (Atkinson, 1993). The identification of TD as a reliable predictor of treatment prognosis is relevant to inform weight loss strategies that can be tailored to leverage treatment effectiveness. In this section, we review studies that measured TD at the beginning of a weight loss program and investigated the association with weight change after completion.

### 6.1. Temporal discounting as a predictor of obesity treatment outcomes

The ability of TD to predict the impact of treatment strategies on weight loss is of great relevance to forecast successful treatment outcomes. Three studies have examined TD and weight loss in association with behavioral weight-loss interventions (Best et al., 2012; Dassen et al., 2018; Manasse et al., 2017). The studies reviewed in this section provide mixed evidence regarding their association.

Two studies have found a significant relationship between TD and weight change. Best et al. (2012) assessed TD in overweight children aged 7–12 years old that were enrolled in a 16-week family-based treatment. The study results indicated a small to medium effect (Cohen's $d = 0.39$) of TD on children's change in percent weight. Children who showed a greater discounting rate at baseline lost less weight by the 9-week time point and the 16-week time point than those who showed a smaller discounting rate at baseline. On average, children with low discounting lost 3.5 kg (5.9 % reduction in weight), while children with high discounting lost 2.3 kg (4.2 % reduction in weight).

Manasse et al. (2017), examined TD in overweight and obese adults, aged 17–80 years old, who were randomized to a 12-month standard

behavioral treatment (SBT) or acceptance-based behavioral treatment (ABT). Overall, participants assigned to the ABT condition showed a greater percent weight loss than participants assigned the SBT condition (i.e., 13.8 % and 9.8 %, respectively) which also had greater rates of weight regain, suggesting that the latter was less effective. Participants in the ABT group who showed a steeper TD at baseline lost more weight at 12 months, while participants in the SBT group lost similar amounts of weight regardless of baseline discounting rate. This study suggests that TD's ability to predict weight loss is moderated by treatment type. Contrary to the authors' hypothesis, steeper TD was associated with greater weight loss. However, the authors discuss that because ABT relies on the ability of a person to make less pleasurable short-term choices to achieve long-term goals, individuals who have a greater focus on short-term options (i.e., greater TD) might respond better to this type of treatment. Furthermore, in cases where a treatment is ineffective (SBT), any outcome marker (TD) could be expected to lack predictive utility.

A single study found no significant relationship between TD and weight change. Dassen et al. (2018) examined whether executive function and TD predicted weight change in individuals with obesity enrolled in a 6-month multidisciplinary weight loss program. Obese participants aged 18–71 years old completed multiple assessments, including TD and the n-back task to assess working memory (Boselie et al., 2016) at baseline. Overall, participants lost an average of 7.22 % of their BMI at baseline, with a range of 1.16 % increase to 23.50 % decrease. The findings revealed that behavioral working memory was the strongest predictor of change in BMI, and although TD exhibited an inverse relationship with BMI change, this relationship was not statistically significant.

Related to this discussion, an additional study examined whether TD predicted dietary lapse risk and whether TD moderated the impact of momentary levels of internal states on dietary lapse occurrence within the first two weeks of a behavioral weight-loss intervention (Manasse et al., 2018). Even though this study did not find a significant main effect of TD on dietary lapse risk, TD significantly moderated the relationship between the internal state of fatigue as measured by the Positive and Negative Affect Scale (PANAS) and likelihood of lapse, such that a stronger relationship was observed among greater discounters. Although lapse risk at the beginning of an intervention might be a limited measure of treatment outcome, studies like this one can reveal behavioral patterns associated with weight problems that could be tackled before or in combination with weight loss initiatives, and, therefore improve its outcomes.

Given the small number of studies and the mixed results regarding TD's ability to predict treatment outcomes, further research is needed to better comprehend the relationship between TD and weight loss in treatment settings. The possibility of modifying TD with effective interventions will be discussed in the next section.

## 7. Measure treatment effectiveness

A fifth utility of a biomarker is the ability to measure treatment effectiveness. Guidelines developed by the Endocrine Society recommend diet, exercise, and behavior modification as the primary components in the management of obesity, with pharmacotherapy and bariatric surgery suggested as an adjunct to amplify adherence to behavior change (Apovian et al., 2015). As described in the previous section, some evidence suggests that discounting rate at baseline may predict weight change following treatment. This section will first review studies indicating that discounting is modifiable among overweight/-obese populations. Second, we will review eleven studies that examined Episodic Future Thinking, an intervention that aims to decrease TD, and its effects on TD and food-related behavior (e.g., fast food demand, food intake, food choice). Third, we will review three studies that examined interventions specifically targeting weight-loss that measured discounting pre- and post-intervention, examining whether changes in TD parallel changes observed in other outcome measures. If discounting rates change in parallel with outcome measures indicating treatment effectiveness, discounting may also serve as a proxy for treatment effect. Much like biomarkers, a behavioral marker for treatment effect could be used to quickly identify novel interventions that are effective.

### 7.1. Temporal discounting is modifiable in overweight/obese populations

The degree with which individuals discount delayed rewards has both trait and state-like characteristics (Odum and Baumann, 2010). That is, evidence suggests TD is relatively stable over time and across situations (Odum, 2011a), but is also modifiable by framing, episodic future thinking, and narratives about various positive and negative environmental contexts (Athamneh et al., 2019; Bickel et al., 2017; Mellis et al., 2018b; Rung et al., 2019). Experimental data extends these findings to overweight/obese individuals (Lewittes and Israel, 1978; Snider et al., 2020; Stein et al., 2017), suggesting that interventions that target or modify TD may provide therapeutic benefit to this population. For example, in one study undergraduates interested in weight-loss showed reduced TD and sugar intake after exposure to scenes of natural versus urban environments (Kao et al., 2019).

### 7.2. Modified by episodic future thinking interventions

Episodic future thinking (EFT) is a narrative intervention derived from the science of prospection. Participants are asked to imagine and list realistic positive future events for various time periods (e.g., 1 month, 6 months, 1 year) and then think about those future events during decision-making tasks. Integrating episodic future events during decision-making increases the value of delayed outcomes (Koffarnus et al., 2013) through increased activation in the executive system (Peters and Büchel, 2010). Thus, EFT is one strategy to help individuals make choices with long-term benefits. Eleven studies of obese/overweight individuals examined whether discounting rates changed in parallel with food-related behavior (e.g., food purchasing, food choice; caloric intake) following an EFT intervention. Five out of eleven studies demonstrated that discounting rates decreased in conjunction with positive changes in food-related behaviors (Athamneh et al., 2020; Daniel et al., 2013; Sze et al., 2017a, 2017b; Daniel et al., 2015; Dassen et al., 2016), while three studies observed improvements in food-related behaviors but no change in TD (Kakoschke et al., 2018; Chang et al., 2020; Hollis-Hansen et al., 2020), two studies noted decreases in TD but no changes in food-related behaviors (Bickel et al., 2020; Stein et al., 2020) and one study found no effect of EFT on discounting, caloric intake, or the relative reinforcing value of food (Mansouri et al., 2020). We discuss these in more detail below.

In an online study, Sze et al. (2017a, 2017b) examined overweight/obese individuals to determine whether EFT reduced TD and hypothetical fast food purchases relative to two control conditions: Episodic Recent Thinking (ERT) and no episodic thinking (i.e., sitting quietly). ERT involves the same procedures as EFT, but participants are asked to list positive recent events rather than future events. Results indicated that EFT significantly reduced TD and demand for fast food while the control conditions had no effect. Furthermore, the positive effects of EFT persisted even when participants were challenged by negative income shock (i.e., abrupt transitions to poverty), which has previously been shown to increase TD.

In a laboratory study, Stein et al. (2020) sought to extend the findings from Sze et al. (2017a, 2017b) to a more clinically advanced population of overweight/obese individuals with prediabetes (i.e., elevated HbA1c) using the same study design and tasks (i.e., EFT/ERT and negative income shock/neutral conditions; hypothetical fast food purchase task; Adjusting TD task). Results indicated that while EFT decreased TD, unlike the prior study EFT did not significantly affect fast food demand. The authors identified several possible confounding demographic factors that might explain the discrepant results between the two studies including differences in age, BMI, and percent of female participants.

The authors also suggested that insulin resistance may blunt the effect of EFT due to its association with increased food reinforcement, thereby diminishing the utility of EFT in those with prediabetes/type II diabetes. Therefore, the authors note it may be necessary to increase the efficacy for more clinically advanced populations by increasing exposure to EFT over time and/or developing adaptations that increase the effect size for this difficult-to-treat population.

Indeed, this conclusion was supported by an earlier laboratory study by Dassen et al. (2016) in a sample of female undergraduates that were not overweight or obese (mean BMI = 22.43; SD = 2.75). Participants were asked to refrain from eating for 2 h prior to the study and were provided snacks *ad libitum* while completing either food-related EFT, food-related episodic past thinking (EPT), non-food-related EFT, or non-food-related EPT. The snacks included chocolate chip cookies, a bowl of M&Ms, and a bowl of syrup waffles. Caloric intake was calculated by weighing the bowls before and after participants generated their episodic thinking cues. Participants then completed a TD task. Both food-related and non-food-related EFT reduced discounting compared to the EPT groups, however only the food-related EFT intervention reduced caloric intake. While change in TD was not related to caloric intake, the results suggested that EFT should be tailored to the behavior of interest.

Of note, a more recent study (Chang et al., 2020) found an interaction between BMI and EFT on ad libitum snacking among first-year psychology undergraduates (mean BMI = 22.65; SD = 4.36), such that EFT reduced unhealthy food intake (chocolate malt balls) in those with high BMI but had no effect on healthy eating (dry oatmeal cereal). The authors noted that discounting did not mediate the relationship between episodic thinking and BMI.

In an attempt to replicate these results in an obese sample, Athamneh et al. (2020) examined the effects of health goals in combination with general EFT on TD and measures of fast food demand and craving in obese individuals. In a 2 × 2 factorial design, participants were randomly assigned to one of four conditions: EFT-health goal, EFT-general, ERT-health goal or ERT-general. Health goal EFT was not more effective than general EFT in reducing TD. However, the addition of a health goal to general EFT was significantly associated with a larger effect on intensity and elasticity of demand for fast food compared to EFT-general. These findings suggest that the amplification of future thinking through the inclusion of a health goal may promote healthy decisions and result in positive behavior changes.

The above findings are consistent with two studies that included a measure of food consumption. Daniel et al. (Daniel et al., 2015, 2013) examined the effect of EFT on TD and energy intake in two parallel human laboratory studies with overweight/obese adult women (Daniel et al., 2013) and overweight/obese 9–14 year old children (Daniel et al., 2015), respectively. In a between-subjects design, participants attended a single two-hour session where they completed a TD task, generated EFT or ERT cues, repeated the TD task, and then completed an *ad libitum* eating task designed to trigger impulsive eating. Both studies demonstrated that EFT reduced TD and caloric intake during the eating task. Interestingly, in both children and adults, EFT had the greatest effect on those individuals who reported the highest desire or drive for food restraint, suggesting that a pre-existing motivation to diet may be an important factor in reducing caloric intake and later weight gain. Furthermore, Daniel et al. (2015) included a comparison group of healthy weight adults and observed that EFT had a similar magnitude effect in both overweight/obese and healthy weight adults.

In a study that measured behavior in both the laboratory and natural environment (Bickel et al., 2020), overweight/obese adults with pre-diabetes completed baseline measures of TD, a food purchase task, and ad libitum food intake procedures. At sessions 2 and 3, participants were prompted to engage in EFT or ERT while completing the same tasks. Further, between the completion of sessions 2 and 3, participants engaged in EFT or ERT at home and completed the TD task remotely. While EFT significantly decreased TD, it did not affect responses on the food purchase task or alter intake in the ad libitum procedure.

Hollis-Hansen et al. (2020) further built on this body of literature by examining the effects of EFT on food purchasing in the natural environment among overweight/obese mothers of children aged 2–15 years. At the baseline visit, participants completed an adjusting amount TD task, played mobile games, and were then randomized to generate cues for EFT or standardized past episodic thinking (SET; vividly re-imagining the experience of playing mobile games). Participants practiced their cues on their own on the evening of the baseline visit and during the next day before and during grocery shopping. On the third day, participants returned to the lab to complete the TD task and provide receipts and short descriptions of all their food purchases. Participants in the EFT group purchased fewer calories, fewer grams of fat, fewer grams of saturated fat and fewer milligrams of sodium than those in the SET group. Although not reaching statistical significance, discounting rates decreased in the EFT but remained stable in the SET group. Of note, participants were not instructed to think about their cues while completing the TD task, which is typically a primary component of EFT.

Mansouri et al. (2020) compared the effects of a single EFT or ERT session relative to daily EFT/ERT on TD, caloric intake during an *ad libitum* buffet, and the relative reinforcing value of food in overweight/obese participants. In a mixed design, participants generated EFT or ERT cues and then completed a TD task while thinking about their cues. Participants were then asked to rate the taste and liking of foods in a buffet consisting of high-energy-dense foods (e.g., chocolate, cookies, potato chips) as well as low-energy-dense foods (e.g., grapes, canned peaches, yogurt). After the taste test, participants were asked to fill out additional questionnaires and were told to eat as much of the buffet as they desired. Participants then received thrice daily EFT cues for 1 week before returning to the lab to complete the tasks again. Relative to the ERT condition, there was no effect of single session or repeated EFT on TD, caloric intake, or the relative reinforcing values of foods. Of note, as baseline measures of these tasks were not completed, the study was only able to conclude that there was no difference in the effects of daily EFT relative to a single engagement of EFT.

Finally, in a pilot study using a within- and between-subjects design, Kakoschke et al. (2018) compared approach-avoidance training (AAT), and EFT delivered daily for one week via smartphone to a control condition among overweight/obese individuals. Food choice and TD were measured at baseline, after seven days of smartphone-delivered training, and at 6-week follow-up. Between-group comparisons indicated that AAT but not EFT significantly increased healthy food choice and modestly reduced weight (Mean difference = -0.74 lbs) from baseline to the six-week follow-up. Neither AAT nor EFT significantly altered TD. However, the authors noted several limitations that may explain the discordant results. First, this pilot study was not sufficiently powered to detect 3 × 2 or 3 × 3 interactions. Furthermore, the authors noted that the EFT procedures were different than those implemented previously. In prior laboratory studies, participants generated cues immediately before completing tasks (i.e., TD and food choice/demand) and were presented with and asked to think about the EFT cues while completing the tasks. In contrast, participants in Kakoschke et al. (2018) generated three EFT cues that were presented daily for seven days and the TD task was completed in a post-training session that was scheduled over 24 h after completion of the EFT training. Additionally, participants were not instructed to think about their event during the task, which is a primary component of EFT. Thus, the procedures may have diminished the effect of EFT on decision-making. The EFT cues also differed from prior laboratory studies, such that participants generated three EFT events for a single time frame (i.e., the next four weeks). Prior laboratory studies have demonstrated that the efficacy of EFT in reducing TD depends on the number of events and future time frames in the task, with multiple events and time frames necessary to observe significant results (Lewittes and Israel, 1978; Snider et al., 2020; Stein et al., 2017). Thus, a number of differences in study design may account for these inconsistent results.

Considered together, these studies provide mixed evidence for the effects of EFT decreasing TD in tandem with changes in food purchasing

and caloric intake. Of note, episodic future thinking interventions are designed to modify temporal discounting and eight out of eleven studies reviewed here indicated that this intervention improved food-related behaviors among overweight/obese individuals. Taken together, the data supports further investigation of EFT as an intervention for obesity, although more research is needed to determine how it can be effectively implemented outside of the laboratory.

### 7.3. Modified by weight-loss interventions

Three studies examined whether the discounting rates of overweight/obese individuals decreased in conjunction with weight following interventions that specifically targeted weight-loss (Kulendran et al., 2017; Sofis et al., 2017; Takada et al., 2011). These studies examined changes in TD and weight after three different interventions including bariatric surgeries, a personalized nutrition/exercise counseling program, and a physical activity intervention. Interestingly, the nutrition/exercise counseling and physical activity interventions demonstrated a parallel decrease in TD and weight, while surgical interventions did not.

Kulendran et al. (2017) aimed to examine whether changes in state-like measures of impulsivity predicted weight loss at 6-months after bariatric surgery. Obese participants, aged 20–69 years old, underwent either a gastric bypass or a sleeve gastrectomy. TD and the Stop Signal Reaction Time Task (SSRT; adapted from Logan et al., 1997) were assessed at least one week before and six months after the surgical procedure. While all participants exhibited large decreases in BMI post-surgery, change in SSRT but not TD predicted change in BMI.

Takada et al. (2011) examined the effects of a 16-week nutrition/exercise advice program on TD and weight loss. Overweight/obese participants were randomized to either self-care or a more intensive and personalized remotely-administered care. The self-care group received an informational packet at baseline and a health exam at week 8 including brief advice, while the telecare group received the same resources plus biweekly remote counseling sessions with a registered nurse who created a personalized weight-loss program for each participant. Weight and a 2-question TD task were measured at baseline, 8-weeks, and 16-weeks (e.g., end of treatment). TD was also measured at a follow-up session 2 months post-treatment. The telecare group significantly reduced weight from baseline to 16 weeks (mean = 4.6 pounds; SD = 2.9; p = 0.001) while the self-care group did not (mean = 1.3 pounds; SD = 3.4; p = 0.42). Interestingly, decreases in TD from baseline to 24-weeks were greater in the self-care condition relative to the more intensive telecare. Given the large variability in weight loss observed in both conditions, the authors noted that only a subset of participants in each condition showed a significant decrease in TD. When these participants were pooled and compared with participants who exhibited no change in TD, only those participants with a significant decrease in TD exhibited significant weight loss.

Finally, Sofis et al. (2017) examined an individually effort-paced physical activity intervention where 12 overweight/obese women met with a fitness coach for 45 min of workout three times per week. Participants first completed a one to two week baseline phase where TD and self-reported minutes of moderate to vigorous physical activity were measured repeatedly until stability in the measures was achieved. In the treatment sessions, participants met with a fitness coach and were instructed to briskly walk laps, alternating between lower effort and higher effort laps (e.g., similar to interval training). After completing the seven-week treatment, participants were instructed to maintain their workouts on their own for one month. Participants' pace (min/mile; calculated by number of 0.17 mile laps completed in each 30 min session) was measured at each treatment session and the one-month follow-up session. TD was also measured three times per week during treatment and again at the one-month follow-up. Results demonstrated that the physical activity intervention significantly increased pace and self-reported daily minutes of moderate activity, and significantly reduced TD. Relative to baseline, TD was reduced by an average of 17.6 % during treatment and 19.9 % during maintenance. Decreases in TD were also significantly associated (r = .71, p = .012) with increases in pace (from baseline to the last workout session (range = 0−3 minute improvement), suggesting that TD may be a good proxy for treatment effect. Furthermore, the positive effects of the intervention remained significant at one-month follow-up, suggesting that changes in physical activity and TD were maintained for some time following the intervention.

The limited number of studies in this section precludes any definitive conclusions. However, the available data suggests that TD changes in response to effective behavioral interventions for overweight/obesity. While two of the three studies reported this result, there were important methodological differences across the studies. First, the primary intervention differed across the studies. Kulendran et al. (2017) investigated biological/surgical interventions while the other two studies investigated behavioral interventions. Although bariatric procedures typically include adjunct behavioral interventions, the primary cause of weight-loss is not behavior change. These results support TD as a putative behavioral marker for obesity, since TD changed in response to behavioral interventions but not biological/surgical interventions. Indeed, Sofis et al. (2017) noted that changes in TD were significantly correlated with sessions attended, such that the more sessions the participants attended, the greater the reduction in TD. Of note, national guidelines recommend that weight-loss interventions are maintained over a period of at least 6-months with 1–2 lbs lost per week (American College of Cardiology/American Heart Association Task Force on Practice Guidelines, Obesity Expert Panel, 2013, 2014). As none of the studies maintained the intervention for the recommended length of time, it is possible that longer interventions would have a greater impact on TD and weight loss. The studies also differed in outcome measures and length of follow-up. Sofis et al. (2017) was the only study that measured behavior change (i.e., increase in physical fitness) in addition to weight loss. Further, Sofis et al. (2017) and Takada et al. (2011) observed that changes in TD were maintained at one and two months post-treatment, respectively. Kulendran et al. (2017) included a 6-month follow-up post-surgery but did not observe any changes in TD. As long-term weight loss outcomes are highly dependent on maintained behavior change, future research may want to include a longer-term follow-up to determine whether TD is a marker for maintained weight-loss following treatment.

## 8. Conclusion

The current review investigated available evidence across a broad range of domains of obesity related research to determine if it supports the characterization of TD as a candidate behavioral marker for obesity. The majority of domains examined (9/12) were generally in support of TD as a behavioral marker for obesity. Of the remaining three domains, two reported mixed results and one reported negative results. We describe these domains and their findings in more detail below.

In terms of functioning as a biomarker: TD was able (in most studies) to identify those at risk for obesity development, determine obesity diagnosis, classify obesity progression, predict treatment prognosis/outcomes, and measure treatment effectiveness. Unfortunately, longitudinal research of discounting and obesity is lacking, limiting the ability to draw conclusions and supporting the importance of conducting this type of research in the future.

In regards to obesity development, studies among children indicated that the ability to delay gratifications is associated with weight gain and obesity onset years later. In addition, heighted TD is associated with lack of interest in, purchasing of, and adherence to healthy diets as well as increased craving and consumption for foods, especially those high in fat and sugar. Heightened TD is also associated with lower levels of physical activity and impaired sleep behaviors. Further interventional studies are needed to investigate whether changes in eating or exercise behaviors

can alter TD rates.

In the context of functioning as a biomarker for disease diagnosis, the large extant literature supports TD as a robust behavioral marker for obesity, with a majority of case-control studies and continuous studies showing a positive relationship between TD and obesity. Additionally, of the studies that suggested no significant relationship between TD and obesity, the majority presented with methodological considerations that may limit the generalizability of findings. In regards to measuring disease severity (i.e., a positive association between TD and BMI), only a few studies have been conducted with all suggesting no relationship between TD and BMI in those already obese. The small number of studies conducted in combination with methodological limitations (e.g., women only samples and restricted age ranges) inhibits the generalizability of these findings. More definitive conclusions await further investigation.

Studies investigating the biological components of obesity and TD indicated that activation of executive function areas, such as the PFC, are related to obesity, weight gain, and TD. Changes in the activation of the executive and/or impulsive systems among the obese was significantly associated with changes in rates of TD. Moreover, published data report a significant association between TD and neurochemical dysregulation, especially dopaminergic neurotransmission. Additional research examining the associations between TD, genetic traits, and dysregulation among other neuromodulators related to eating and exercise modulation in obese individuals is needed to enhance our understanding of the biological substrates of TD and obesity.

Research studies examining TD's ability to classify risk for obesity progression and/or comorbidity complications are limited. Few studies with different methods examine the ability of TD or delay of gratification to predict weight change over time observing mixed findings. Overall, obesity related comorbidities are associated with greater rates of TD than obesity alone. Further longitudinal research and research investigating other comorbidities related to obesity and different severities of comorbidities would help to further elucidate TD's ability to predict the progression of obesity.

Mixed evidence was found regarding whether TD may serve as a proxy for obesity treatment outcomes; some evidence suggests that baseline TD predicted treatment outcomes. However, due to the limited number of studies, the relationship between baseline TD and weight loss in treatment settings needs more exploration.

Lastly, TD may be modified during treatment, which could obscure the predictive validity of baseline TD. Indeed, the evidence suggests that discounting and food-related behaviors can be modified by Episodic Future Thinking in overweight/obese individuals. Behavioral weight-loss interventions also provided some evidence of concurrent decreases in TD and weight during treatment. However, the limited number of studies examining discounting's ability to function as a determinant of treatment outcomes highlights the importance of additional research in this area.

In conclusion, this review examined the candidacy of TD as a behavioral marker for obesity across 153 published studies. Given the positive relationship for TD in 9 out of 12 domains examined, further consideration for TD as a behavioral marker of obesity is warranted. Several domains possess a small number of studies and more research in these areas will help to provide more definitive conclusions. While obesity is clinically diagnosed using BMI, this simple conceptual framework may not fully capture the range of maladaptive behaviors (e.g. eating patterns) that contribute to obesity. Future research may benefit from including measurements of these constructs (i.e., binge eating behaviors). If future research supports the classification of TD as a candidate behavioral marker for obesity, TD could be useful to identify and target individuals at greater risk of developing obesity, predict treatment outcomes, reveal facets of the disorder's mechanism, and suggest novel targets for treatment development.

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## Declaration of Competing Interest

Although the following activities/relationships do not create a conflict of interest pertaining to this manuscript, in the interest of full disclosure, Dr. Bickel would like to report the following: W. K. Bickel is a principal of HealthSim, LLC; BEAM Diagnostics, Inc.; and Red 5 Group, LLC. In addition, he serves on the scientific advisory board for Sober Grid, Inc., Ria Health, is a consultant for Alkermes, Inc, and is conducting research supported by Indivior. The other authors report no conflict of interest.

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