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A Reinforcer-Pathology Model of Health Behaviors in Individuals with Obesity

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Abstract

Objectives: Research concerning trans-disease processes aims to ascertain an underlying mechanism of several, seemingly dissonant behaviors and/or pathological conditions. The theory of Reinforcer Pathology posits that excessive delay discounting and the maladaptive over-valuation of a particular commodity underlie a variety of dysfunctional health behavior ranging from substance abuse to overeating and financial responsibility. The present study extends recent health behavior research by examining the extent delay discounting and food valuation correlate with engagement in a latent factor model of health and financial behaviors among healthy-weight participants and participants with obesity using the Health Behaviors Questionnaire.

Methods: A total of 700 participants (n=340 BMI<30, n=360 BMI>30 kg/m^2) were recruited using Amazon Mechanical Turk. Participants completed a monetary delay discounting assessment, the Health Behaviors Questionnaire, and two measures of food valuation: Behavioral economic demand and the Power of Food scale (PFS).

Results: Utilizing structural equation modeling, both delay discounting and food valuation significantly correlated with engagement in health and financial behavior for both groups. The comparison of latent factors between groups indicated that participants with obesity were less likely to engage in multiple health behaviors and that these differences can be partially attributed to differences in delay discounting and food valuation.

Conclusion: These results replicate previous research and further support the role of delay discounting as a trans-disease process. Given these results, trans-disease interventions, such as episodic future thinking, designed to specifically target reinforcer pathology may have a profound effect on overall functioning.

Keywords

Delay Discounting; Food Valuation; Health Behaviors; Structural Equation Modeling; Behavioral Economic Demand; Power of Food

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COMPETING INTERESTS
WBD and DAP report no conflicts of interest. SES and WKB are principals of BEAM Diagnostics, Inc. In addition, WKB is a principal of HealthSim, LLC; Notifius, LLC; and Red 5 Group, LLC. WKB also serves on the scientific advisory board for Sober Grid, Inc.; Ria Health; US WorldMeds, LLC; and is a consultant for Alkermes, Inc. and Nektar Therapeutics.

INTRODUCTION

The study of trans-disease processes aims to identify an underlying mechanism of seemingly discordant behaviors and/or disease states (Bickel et al., 2019; Bickel, Jarmolowicz, Mueller, Koffarnus, & Gatchalian, 2012; Bickel, Quisenberry, Moody, & Wilson, 2015). That is, in contrast to contemporary disease study in which each disease has a unique etiology, the study of trans-disease processes supposes that the etiology of one disease could inform others (Bickel and Mueller 2009; Bickel et al. 2012). For example, a trans-disease process could explain separate maladaptive behaviors, such as overeating and not engaging in physical exercise. Importantly, identifying trans-disease processes could provide targets for intervention that could have permeating effects. One such process, excessive delay discounting, has been demonstrated to undergird a variety of maladaptive health behaviors including alcohol and substance abuse, risky sexual behavior, gambling, obesity and overeating, financial irresponsibility, medical non-adherence, as well as a variety of others (Amlung, Petker, Jackson, Balodis, & MacKillop, 2016; Amlung, Vedelago, Acker, Balodis, & MacKillop, 2016; Bradford, 2010; Celio et al., 2016; Chesson et al., 2006; Daugherty & Brase, 2010; Garza, Ding, Owensby, & Zizza, 2016; MacKillop et al., 2011; Petry, 2001; Snider, DeHart, Epstein, & Bickel, 2019).

Delay discounting is the process by which the subjective value of an outcome is diminished as the delay to its receipt increases. This process (i.e., the rate of decline in value of delayed rewards) may be measured using a delay discounting task in which individuals are offered a titrating set of binary choices between a smaller reward available immediately or a larger reward available after some delay. Universally, if the delay becomes too long, the *subjective* value of the immediate option will outweigh the delayed option (although still more *objectively* valuable). However, individuals who excessively discount future rewards (i.e., choose the smaller sooner option more often and at shorter delays) are those at the most risk for engaging in mal-adaptive behaviors (Amlung, Petker, et al., 2016; Bickel, Jarmolowicz, Mueller, & Gatchalian, 2011; MacKillop et al., 2011; Snider et al., 2019). Interestingly, delay discounting has also been demonstrated to be consistent across commodities. That is, high discounters for money are also high discounters for food, alcohol, or cigarettes suggesting it as a ‘personality trait’ (Odum 2011). The theory of Reinforcer Pathology posits that excessive discounting of the future in combination with the maladaptive over-valuation of an individual’s commodity of choice, such as drugs or food, produces the greatest severity of risk (Bickel et al., 2011; Bickel, Johnson, Koffarnus, MacKillop, & Murphy, 2014). In fact, reinforcer pathology has recently been suggested as an addiction-relevant biomarker to be targeted across many different commodities (Kwako et al. 2018). This interaction between delay discounting and valuation was first observed in substance abuse (Bickel et al. 2011) and, more recently, in obesity (Carr, Daniel, Lin, & Epstein, 2011). For example, when female participants with obesity were presented with palatable foods in a laboratory setting, the interaction of delay discounting rates and food reward sensitivity (i.e., food stimuli-elicited pleasure and motivation to eat; a facet of value), as measured by the Power of Food Scale (PFS), significantly predicted total calories consumed (Appelhans et al., 2011). In other words, individuals with the greatest discounting rates and highest sensitivity to food consumed the greatest number of calories (Appelhans et al., 2011). Moreover, Rollins et al. (2010) demonstrated similar findings in which delay discounting rates moderated the effect that reinforcing value of food, as measured by the maximum effort an individual is willing to exert to obtain one serving of food, had on total caloric intake among healthy weight females. Females with high value and discounting rates consumed more than did females with high value and low discounting rates.

The current study extended the results from a recent study conducted in cigarette smokers. Snider and colleagues (2019) examined the extent to which delay discounting correlated with engagement in a latent factor model of health and financial behaviors based on a novel Health Behaviors Questionnaire. In summary, the study found that among cigarette smokers, delay discounting significantly correlated with engagement in maladaptive health and financial behaviors, irrespective of smoking status. While an important contribution to the field of trans-disease processes, the study did not include a measure of value for cigarettes, precluding an examination of reinforcer pathology. Therefore, given the support for the reinforcer pathology framework in obesity, the present study aimed to build latent factor models of the same health and financial behaviors, but in both healthy weight participants and participants with obesity (a novel population for evaluating the Health Behaviors Questionnaire). We expect differences in delay discounting and food valuation to account for the differences in health behaviors between healthy-weight participants and participants with obesity.

MATERIALS & METHODS

Participants

Seven-hundred participants (n=340 BMI < 30 kg/m^2, n=360 BMI > 30 kg/m^2) were recruited via Amazon Mechanical Turk (mTurk) and paid $4.00 for completing the survey. mTurk is a crowdsourcing platform in which individuals can complete tasks for monetary compensation. In order to qualify, participants had to have completed at least 50 mTurk assignments with a 90% approval rating or higher. Participant demographics are presented in Table 1. Groups were divided using the >30 BMI kg/m^2 cut-point for Class 1 obesity as defined by the Centers for Disease Control and Prevention (CDC). No significant differences in demographics were identified between groups apart from the BMI difference (see Results). The Virginia Tech Institutional Review Board reviewed and approved all procedures.

Procedure and Assessments

In order to qualify for the experiment, all participants had to complete a brief six-question screening questionnaire at the beginning that included questions about their substance use, height, and weight. The screening questionnaire did not indicate which specific questions would be used to determine eligibility. All eligible participants completed a delay-discounting task, followed by the Health Behaviors Questionnaire, a behavioral economic demand task for the participant’s favorite food, and the Power of Food questionnaire.

Delay Discounting Task—Delay discounting was assessed using an adjusting-amount task (Du, Green, & Myerson, 2002), during which participants were presented with the choice between a smaller, immediate outcome and a larger, delayed outcome (here, hypothetical monetary rewards). Participants were first presented with repeated hypothetical choices between $50 now or $100 at a delay. The immediate amount was then adjusted (decreased if the immediate amount was selected and increased if the delayed amount was selected) after the first trial by $25. The subsequent five adjustments were half of the previous adjustment (e.g., $12.5, $7.25, etc.). The amount of the immediate outcome after the seventh, and final, adjustment served as the indifference point for the specific delay test. Seven discrete commonly selected delays were used:1 day, 1 week, 1 month, 3 months, 1 year, 5 years, and 25 years (Du et al. 2002; Snider et al., 2019).

Health Behaviors Questionnaire—Participants completed the Health Behaviors Questionnaire, which comprises a series of 61 items (Snider et al., 2019) that assess the relative frequency with which participants engage in common health and financial behaviors categorized as “Drug Use”, “Finances”, “Fitness”, “Food”, “Health”, “Household Savings”, “Personal Development”, or “Safe Driving”. The complete Health Behaviors Questionnaire is listed in the Supplemental Materials. Internal consistency was acceptable in the current sample (Cronbach’s alpha = 0.85).

Behavioral Economic Demand—Demand for the participant’s preferred food was measured by first asking the participant to report their favorite snack food. Snack foods were defined as items typically found in a vending machine (e.g., chips, pretzels, candy bars) to better standardize serving size and snack type. Participants were then instructed to indicate how many servings of their favorite snack food they would purchase at the following prices: $0.01, $0.05, $0.10, $0.25, $0.50, $1.00, $5.00, $10.00, $20.00, $40.00, and $80.00 (Koffarnus et al. 2015; Snider et al. 2019). At each price, participants were asked to imagine that they had to consume what they purchased within 24 hours, had no other access to that food, and could not share what they purchased with anyone else.

Power of Food Scale (PFS)—Finally, participants completed 21-item Power of Food Scale (Lowe et al., 2009) which assessed the psychological impact or hedonic/reinforcing value of food. Thus, the PFS scale delineates the appetitive drive to obtain food from the tendency to eat, or overeat, food (Davis et al., 2011). A summary score was calculated as the arithmetic mean of responses to all 21 items. Internal consistency was excellent in the current sample (Cronbach’s alpha healthy weight participants = 0.95, Cronbach’s alpha participants with obesity = 0.96, Cronbach’s alpha all participants = 0.96).

Analyses

Delay Discounting and Demand—The results of the delay-discounting task were analyzed by fitting the equation (Mazur, 1987):

$$V = A/(1 + kd)$$

where V is the indifference point at a given delay, A is the amount of the delayed outcome, d is the delay, and k quantifies the rate at which the outcome loses value as a function of delay. k is was log transformed (lnk) to improve its parametric properties. The results of the food demand task were analyzed by fitting the equation (Koffarnus, Franck, Stein, & Bickel, 2015):

$$Q = Q_{0*}10^{\wedge}k\left(e^{\wedge} - aQ_0C - 1\right)$$

where Q is the dollar amount spent at a given price, C is the price of the food item, Q_0 represents demand intensity or the model fit y-intercept (e.g., purchasing at zero cost; upper bound set to 1), k is a constant and is the range of the function in logarithmic units (obtained from the empirical range + 0.5; set to 7.97 in these analyses), and α represents demand elasticity or the decrease in purchasing as price increases. Demand curves were fitted using the beezdemand package in R (Kaplan, n.d.; Team, 2018).

Structural Equation Modeling (SEM)—In order to assess the degree to which delay discounting, food valuation, and eating behaviors correlated with the large panel of health-related behaviors in healthy-weight participants and participants with obesity, structural equation modeling (SEM) was used (Hox, Moerbeek, & van de Schoot, 2010; Snider et al., 2019). SEM is a more appropriate analytic technique for investigating complex relationships than a bivariate correlation matrix for two reasons. First, SEM controls for the shared error variance among measured variables, resulting in a more accurate description of the covariance between variables. Therefore, SEM models present an error-controlled accounting for how variables are related. Second, SEM allows for the grouping of measured variables into theoretically relevant latent factors which can then be correlated with other measured variables or latent factors.

The quality of a model fit is commonly assessed using several goodness-of-fit indicators. First, a chi-square test is conducted as an indicator of model misfit. A non-significant chi-square value indicates that the model accounts for a sufficient amount of covariance in the data. The Tucker Lewis Index (*TLI*) is a ratio of the chi-squared value of the theoretical model fit relative to a null model (now covariance among measured variables). The root mean square error of approximation (*RMSEA*) assesses how far the theoretical model fit is from a perfect model fit. The standardized root mean square residual (*SRMR*) is the “average” difference between the implied (theoretical model) and observed covariance accounted for by the latent factors. For the structural model (latent factor groupings without regression paths), predictor variables were grouped into the same latent factors established in a previous validation of the Health Behaviors Questionnaire by Snider et al. (2019); that is, drug use, finances, fitness, food, health, household savings, personal development, and safe-driving. Statistically significant factor loadings establish the concurrent validity of the question by reflecting the item’s covariance with other items that load onto the same factor.

For the regression model, delay discounting, food demand intensity, and Power of Food scores served as predictor variables. Importantly, because of the very strong correlation between demand intensity and demand elasticity (and the subsequent instability introduced into the final model), demand elasticity was not included in the SEM models. In models where elasticity replaced intensity, elasticity did not predict the latent factors. Because most of the variables were measured on ordinal Likert scales (see Supplemental A), diagonally weighted least-squares (DWLS) estimation was used which allows for polychoric covariance estimations (Li, 2016).

In order to allow for the comparison of the latent factors and regression paths between groups, a structural latent model was tested for (e.g., healthy-weight participants and participants with obesity) model invariance. The purpose of this process is to confirm that the same latent structure exists between healthy-weight participants and participants with obesity. This process entails gradually constraining the factor loadings, factor intercepts, residuals, factor variances, and factor covariances between groups so that the latent factors of the final model are conceptually equal between groups.

Six health behavior questions were removed from the SEM model in order to achieve model convergence and improve the quality of the latent factors (see supplemental material Table 1S for identification of removed questions). These variables were removed for either correlating too strongly with other measured variables of that same factor (e.g., $r^2 > 0.90$), they did not significantly correlate (e.g., $r^2 < 0.10$) with any measured variables in the data set, or there was no variability in the responses to account for (e.g., nearly all participants reported always wearing their seatbelt). The remaining 55 measured variables were included in the final SEM. For each latent factor, the reference variable was specifically chosen so that positive correlations with the latent factor and delay discounting would reflect more frequent engagement in risky or problematic behaviors and negative correlations with the latent factor and delay discounting would reflect more frequent engagement in health-positive behaviors.

Two values for the correlation between factors are reported and discussed. The first value is the correlation between factors without the regression equations. This value represents the full correlation between the latent factors. The second value is the residual correlation which is the correlation between factors after the unique variance accounted for by the predictor variables (i.e., delay discounting) is accounted for. All SEM analyses were conducted using the lavaan package (Rosseel, 2012) in R.

Finally, though not reported here, we conducted two additional exploratory models. The first was to test delay discounting as a mediator of the relationship of food valuation (e.g., demand intensity and Power of Food) to the latent variables and the second was to investigate delay discounting as a moderator of food valuation. Neither model confirmed these hypotheses.

RESULTS

Demographics

Participant demographics were compared using t-tests and chi-square tests when appropriate (Table 1). Statistically significant differences in food demand intensity (Q_0; $t(696) = 3.53$, $p = 0.0004$, CI [0.16, 0.55], $d = 0.26$), *lnk* ($t(696) = 2.63$, $p = 0.009$, CI [0.11, 0.75], $d = 0.19$), and Power of Food ($t(696) = 7.80$, $p = 2.16e\text{-}14$, CI [8.70, 14.55], $d = 0.59$) were observed with participants with obesity reporting demand for food, delay discounting, and PFS scores. No other differences in participant demographics were found.

SEM Results

First, the structural latent model was tested for (e.g., healthy-weight participants and participants with obesity) model invariance. The purpose of this process is to confirm that the same latent structure exists between healthy-weight participants and participants with obesity. An unrestricted measurement model was first created in which all latent factor intercepts and loadings were allowed to differ between groups and no regression paths were included (X^2 (2,800)= 5,577, $p = 0.0001$, $TLI = 0.950$, $RMSEA = 0.053$, $SRMR = 0.086$). In this model, the latent factors cannot be interpreted as reflecting the same processes between groups because the covariance they account for among the observed variables differs. Overall, the model fit indices support the quality of the measurement model.

Second, delay discounting, demand intensity, and PFS scores were added as correlates of the latent factors. Additional variables did not significantly correlate with the latent factors, including demand elasticity, or their inclusion made the final model unstable and are therefore not included in the reported model. Again, an unrestricted model was created (X^2 (3,082)= 895.209, $p = 1.00$, $TLI = 2.376$, $RMSEA < .001$, $SRMR = 0.097$), suggesting that the addition of the regression paths greatly improved the overall model fit.

Finally, structural invariance was increasingly tested (e.g., constraining of the factor loadings, factor intercepts, residuals, factor variances, and factor covariances between groups) by comparing the quality of the model fit of the configural model (all values free to vary between groups; see model fit indices above) to the structurally invariant model. The difference in the quality of fits between the configural model and the most strict structurally invariant model (X^2 (3,305)= 1,008.255, $p = 1.00$, $TLI = 2.301$, $RMSEA <$ .001, $SRMR = 0.099$) was not statistically significant ($\Delta X^2 = 204.62$, $p = 0.806$) indicating that increasing the model invariance did not significantly decrease the quality of fit. This finding indicates that the measured variables were highly reliable and that the latent factors measured the same constructs in healthy-weight participants and participants with obesity. This also allowed us to compare the latent factor means and regression paths between groups. Importantly, while the unstandardized factor loadings will be held constant between groups, the standardized loadings, which reflect the amount of variance accounted for by the factor, may differ between groups.

Structural Model—The 55 health behavior questions were organized into eight latent factors: Finances, Fitness, Food, Health, Household Savings, Personal Development, Risky Behaviors, and Safe Driving. All eight factors significantly correlated with their corresponding measured variables (Figure 1; see Supplemental Materials Table 2S for complete model results). The mean R^2 value for each group was 0.32 ($sd = 0.21$) indicating that the latent factors accounted for a similar amount of variance between the two groups.

Regression Model—Three measured variables (Table 2; see Supplemental Materials Table 2S for complete model results) were found to significantly correlate with the latent factors: delay discounting, demand intensity (Q_0), and PFS scores. These three variables were not strongly correlated and only demand intensity and PFS scores were significantly correlated ($r = 0.17$, $p < .001$, $r^2 = .03$) but this significant relationship may be an artifact of the large sample size as indicated by the small effect size. Delay discounting significantly correlated with most latent factors for both groups (Figure 2). Furthermore, because a structurally invariant model was tested, the number of significant regression paths could be compared between groups to determine which measure of food valuation was a better correlate because the latent factors represent the same construct. In healthy-weight participants, demand intensity was a stronger correlate (as determined by the number of significant paths) with the latent factors than PFS scores whereas, in participants with obesity, PFS scores were a better correlate with the latent factors than demand intensity.

Of note, the direction of the relationship with delay discounting and the latent factors was as expected. For latent factors in which lower scores donated poorer behavioral choices, the relationship with $\ln k$ (e.g., delay discounting; the more negative the value, the less the discounting) was negative meaning that as delay discounting decreased, engagement in positive health behaviors increased. Likewise, the relationship of demand intensity and Power of Food scores to the latent factors was also in the expected direction. As food valuation increased, so did engagement in unhealthy behaviors.

Latent Factor Means—First, the group means were compared using only the structural model (e.g., no regression paths). Participants with obesity reported less healthy food choices ($z = 4.57$, $p < .001$), less safe driving habits ($z = 2.21$, $p < .03$), poorer fitness habits ($z = -7.09$, $p < .001$), poorer health habits ($z = -2.75$, $p < .01$), poorer financial habits ($z = -6.47$, $p < .001$), poorer personal development ($z = -4.27$, $p < .001$), and greater engagement in risky behaviors (e.g., drug use; $z = 4.22$, $p < .001$) but no difference in household savings behaviors was found ($z = 1.61$, $p = 0.12$).

Importantly, by adding the regression paths to the full model, no latent factor mean differences were found between groups indicating that the differences in latent factors can in part be attributed to the group differences in delay discounting, demand intensity, and PFS scores.

DISCUSSION

The present results reinforce those previously reported by Snider, DeHart, Epstein, and Bickel (2019) and further support the role of delay discounting as a trans-disease process (Bickel et al., 2019; Snider et al., 2019) and key behavioral marker of maladaptive health behaviors. In addition, delay discounting and food value together correlated with engagement in health and financial behaviors. Unlike previous work, latent model results have not been compared between two groups, healthy-weight participants and participants with obesity.

The latent variables accounted for a significant portion of the health-behavior questions. Importantly, strict structural invariance (i.e., factor loadings and intercepts held constant) was achieved indicating that the health-behavior questions measured the same constructs between the two groups. Therefore, the latent factors represented comparable constructs. This finding further establishes the construct validity of the health-behavior questions within the Health Behavior Questionnaire though further research is needed to refine, add, and remove questions.

Because structural invariance was achieved, the latent factor means between groups could be compared. Before adding the regression paths, most latent factors (except for household savings) were different between the groups (i.e., health-weight and participants with obesity), wherein the latter universally reported less engagement in healthy behaviors. However, when the regression paths were added, the latent means were no longer different. This finding suggests that the differences in engagement in health behaviors between healthy-weight participants and participants with obesity can, in part, be attributed to differences in their delay discounting, demand for food, and their propensity to engage in uncontrolled eating (i.e., their reinforcer pathology). Additionally, the explanation for the initial lack of difference in household savings (before inclusion of regression paths) is unknown. The similarity in household savings behaviors may reflect regional variability (e.g., using air conditioner or heater) in both groups that in turn diminishes the likelihood of identifying differences between groups.

The study of the phenomenon of delay discounting is becoming increasingly popular in the literature. The total number of manuscripts with the keyword of “delay discounting” has increased 4-fold in the past 10 years (since 2010), based on a PubMed search. As described above, delay discounting is significantly associated with a multitude of other negative health and financial behaviors (Amlung, Petker, Jackson, Balodis, & MacKillop, 2016; Amlung, Vedelago, Acker, Balodis, & MacKillop, 2016; Bradford, 2010; Celio et al., 2016; Chesson et al., 2006; Daugherty & Brase, 2010; Garza, Ding, Owensby, & Zizza, 2016; MacKillop et al., 2011; Petry, 2001; Snider, DeHart, Epstein, & Bickel, 2019). In addition, the rate of an individual’s discounting can be a significant predictor of engagement with, current use of, relapse risk for, and treatment success from substances of abuse (Bickel et al. 2014). From a neuroeconomics perspective, others have demonstrated that when completing a delay discounting task in an fMRI, impulsive decision system regions (i.e., limbic and paralimbic) became more activated when making choices for immediately available rewards. In contrast, when making decisions for delayed rewards, executive decision system regions (prefrontal cortex) were more activated (McClure et al. 2004). From the perspective of the Competing Neurobehavioral Decision Systems Theory, excessive delay discount rates are a product of an imbalance between the impulsive and executive decision systems (Bickel et al. 2011). Therefore, interventions that decrease the impulsive decision system activation or increase the executive decision system activation are hypothesized to resolve the relative imbalance and produce more self-controlled behavioral outcomes (Koffarnus et al. 2013). One unexpected finding was that the two food value assessments (i.e., demand and power of food) differentially correlated with engagement of health behaviors in the healthy-weight participants and participants with obesity. That is, food valuation, described by intensity of demand, correlated with engagement in health behaviors in 7 of 8 of the latent factors in the healthy-weight participants, compared to only 1 of 8 (i.e., the food factor) in participants with obesity. In contrast, food valuation, as measured by the PFS, correlated with 5 of 8 factors in participants with obesity, compared to 3 of 8 factors in the healthy-weight participants.

Food valuation is a multi-faceted construct that may include food-seeking (e.g., effort exerted to obtain food, cost) and food-consuming (e.g., appetite for available food, ingesting) behavior, in addition to other processes (Tang, Fellows, & Dagher, 2014). Thus, the demand task measured food valuation as the cost to obtain a single food item (i.e., food-seeking), while the PFS scale measured food valuation as the propensity to eat uncontrollably given currently available foods (e.g., appetite). Given that demand intensity and PFS scores differed between the groups, the two groups may differ in both food-seeking and food-consuming behavior, and, therefore, may display differential sensitivity to the two food valuation assessments. Importantly, demand intensity and PFS scores correlated but with a clinically insignificant effect size ($r^2 = 0.03$) validating that they are measuring different facets of food valuation. Given that reinforcer pathology includes the interaction between the temporal window and food valuation, perhaps these facets of valuation should be considered in future iterations of reinforcer pathology theory. Moreover, regardless of the differences observed in the roles of the two measures of food valuation in the present study between the two groups, reinforcer pathology may be an underlying trans-disease mechanism of decision-making regarding health and financial behaviors.

Some limitations to the current results do exist. The health behavior questions are based on face-valid, societally-based values and are still in the early stages of development. While their construct validity has now been twice validated (Snider et al., 2019), further refinement is needed. For example, several questions were removed from the final model because of their failure to fit a theoretically valid latent factor. Another point of future research is to understand the remaining unexplained variance of the health behaviors (Table S1). Additional questions such as "Pay for your own health insurance?" (FIN2) will be reworded for clarity. While this model accounts for a significant amount of variance, other processes are needed to give a more complete understanding of the underlying mechanisms of different health and financial behaviors. Finally, we recognize that our defined groups did not differentiate the difference between "healthy-weight" (i.e., 18.5 to <25 BMI kg/m^2) and "overweight" (i.e., 25.0 to <30 BMI kg/m^2) or obesity (30.0 to <40 BMI kg/m^2 and morbid obesity (>40 BMI kg/m^2). While future work may aim to identify differences among these three groups, we note that 52% of our sample reported a >30 BMI kg/m2, which aligns with recently estimated obesity prevalence in the US (~40%)(Fryar et al. 2018; Flegal et al. 2016).

The value of the identification of trans-disease processes is their potential to serve as targets of intervention. That is, interventions designed to specifically target reinforcer pathology may have a profound effect on overall functioning. One such intervention is Episodic Future Thinking (EFT), increases activation of the executive system activation (Peters and Büchel 2010) by promoting the vivid prospection of positive future events. Previous work has demonstrated that encouraging participants to engage in EFT decreases both delay discounting and value of food and other substances of abuse (Daniel, Said, Stanton, & Epstein, 2015; Snider, LaConte, & Bickel, 2016), which suggests its potential in impacting many disease states by targeting one process - reinforcer pathology. EFT is an example of one way an individual struggling with multiple maladaptive behaviors may find assistance on several fronts at once. Future work may find the best ways to administer this intervention or identify new ones. In sum, this trans-disease holistic approach to behavioral change presents a rich and important opportunity for future research and potentially more viability in therapeutic treatments.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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WBD and DAP report no conflicts of interest. SES and WKB are principals of BEAM Diagnostics, Inc. In addition, WKB is a principal of HealthSim, LLC; Notifius, LLC; and Red 5 Group, LLC. WKB also serves on the scientific advisory board for Sober Grid, Inc.; Ria Health; US WorldMeds, LLC; and is a consultant for Alkermes, Inc. and Nektar Therapeutics.

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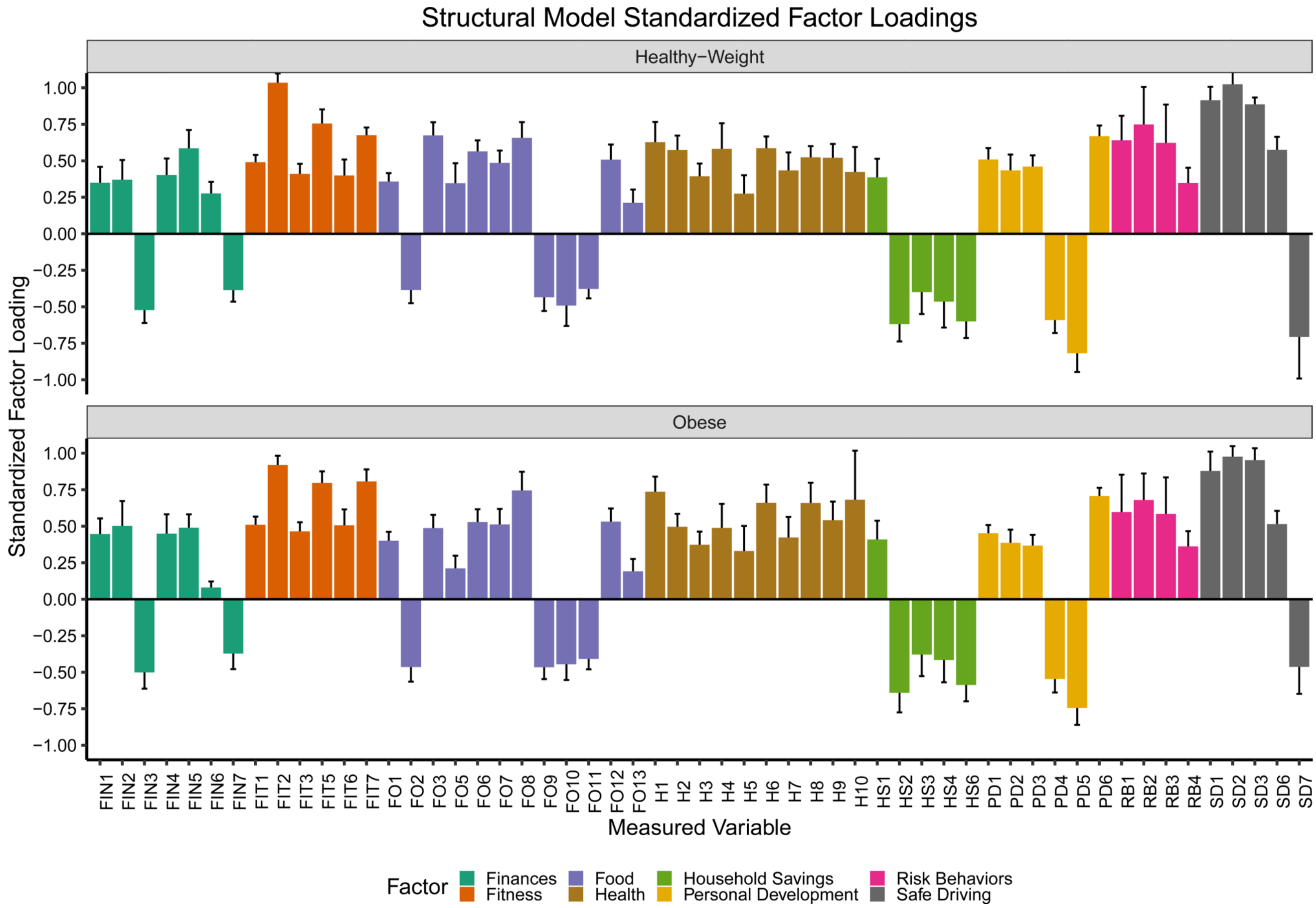

Figure 1.

Standardized factor loadings for healthy-weight participants and participants with obesity.

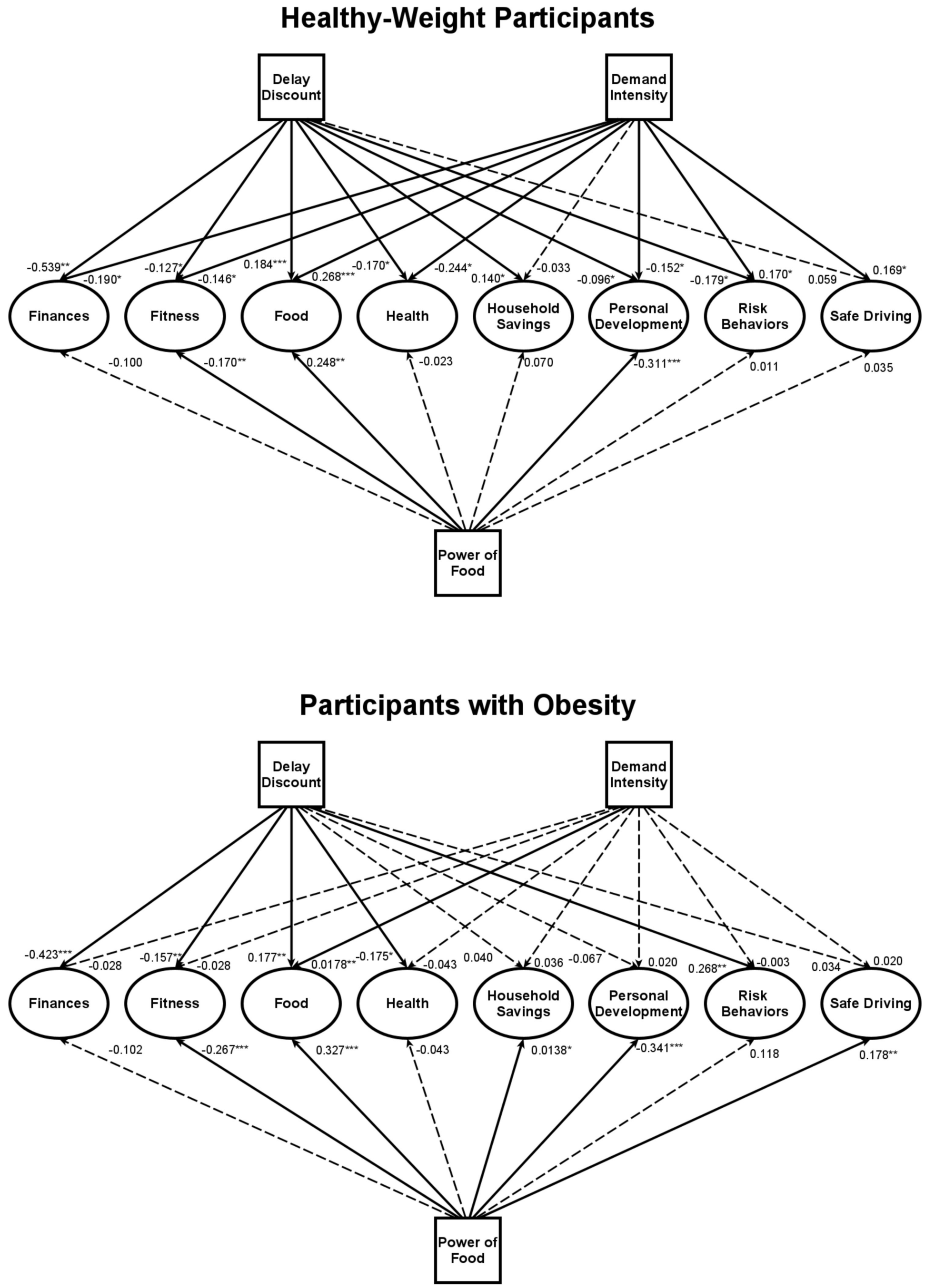

Figure 2.

Regression model for healthy-weight participants and participants with obesity. Solid line denotes a statistically significant path. Values are standardized coefficients.

Table 1.

Participant Demographic Means and Standard Deviations By Group.

	Healthy Weight	Obese	Total
Age	37.89(13.12)	36.75(10.91)	37.32(12.03)
BMI	24.21(3.53)	37.43(7.96)	31.03(9.08)
Education (Years)	13.58(1.32)	13.93(1.39)	13.73(1.35)
Sex (% Female)	68.84%	61.56%	65.08%
Income (Median)	$50,000($37,888)	$40,000($37,797)	$45,000($37,876)
Race (% Caucasian)	73.87%	77.59%	75.79%
Relationship Status (% Single)	25.12%	24.06%	24.57%

Table 2.

SEM Regression Paths.

Latent Factor	Healthy-Weight			Obese		
	Ink	Demand Intensity	PoF	*Ink*	Demand Intensity	PoF
Finances	−0.539 **	−0.190 *	−0.100	−0.423 ***	−0.028	−0.102
Fitness	−0.127 *	−0.146 *	−0.170 **	−0.157 **	−0.028	0.267 ***
Food	0.184 ***	0.268 ***	0.248 **	0.177 **	0.178 **	0.327 ***
Health	−0.170 *	−0.244 *	−0.023	−0.175 *	−0.043	−0.043
Household Savings	0.140 *	−0.033	0.070	0.040	0.036	0.0138 *
Personal Development	−0.096 *	−0.152 *	−0.311 ***	−0.067	0.020	0.341 ***
Risk Behaviors	1.79 *	0.170 *	0.011	0.268 **	−0.003	0.118
Safe Driving	0.059	0.169 *	0.035	0.034	0.020	0.178 **

* p <.05.

** p < .01.

*** p <.001