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A dual-process approach to exploring the role of delay discounting in obesity

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Running title: Dual-parameter model for obesity related delay discounting

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Abstract

Delay discounting of financial rewards has been related to overeating and obesity. Neuropsychological evidence supports a dual-system account of both discounting and overeating behaviour where the degree of impulsive decision making is determined by the relative strength of reward desire and executive control. A dual-parameter model of discounting behaviour is consistent with this theory.

In this study, the fit of the commonly used one-parameter model was compared to a new dual-parameter model for the first time in a sample of adults with wide ranging BMI. Delay discounting data from 79 males and females (Males=26) across a wide age (M=28.44 years (SD=8.81)) and BMI range (M=25.42 (SD=5.16)) was analysed. A dual-parameter model (saturating-hyperbolic; Doya, 2008) was applied to the data and compared on model fit indices to the single-parameter model.

Discounting was significantly greater in the overweight/obese participants using both models, however, the two parameter model showed a superior fit to data ($p<.0001$). The two parameters were shown to be related yet distinct measures consistent with a dual-system account of inter-temporal choice behaviour.

The dual-parameter model showed superior fit to data and the two parameters were shown to be related yet distinct indices sensitive to differences between weight groups. Findings are discussed in terms of the impulsive reward and executive control systems that contribute to unhealthy food choice and within the context of obesity related research.

Keywords: Obesity, delay discounting, dual-process, two-parameter, model

1. Introduction

The ability to delay gratification may be crucial for exerting self-control in a tempting food environment. The conflict between the delayed rewards of good health and weight maintenance versus the immediate reward of tasty foods is a dilemma well captured by the delay discounting task [1]. Typically, participants are presented with a choice between a small reward available immediately, or a larger reward available after a delay. Several trials are presented over a number of delay periods and an indifference point (IP) is calculated as the value at which the participant is indifferent to the reward being received now or after a delay. The lower the IP values, the less an individual is willing to wait for the reward, indicating a reduced ability to delay gratification. Discounting of the future on both money and food-based tasks has been related to over eating and obesity, albeit inconsistently [2-15]. A commonly used model of discounting outcomes in obesity research is the single parameter (k) hyperbolic model [16] which is fitted to data using the formula:

$$\mathrm{V} = \frac{\mathrm{A}}{1 + k\mathrm{D}}$$

Where: V is the Indifference Point (IP), A is the Larger Later Reward (LLR), D is the delay (days) and k is the free parameter for estimating steepness of temporal discounting.

As delays increase the IPs typically decrease as respondents are willing to accept less money immediately instead of waiting for the delayed reward. This decline is however time-inconsistent, being steeper when the delays are proximal (one day versus one week) and shallower when delays are more distal (six months versus nine months). This enhanced sensitivity to differences between shorter compared to longer delays may be reflecting a reduced ability to imagine distal time periods with the same clarity as the near future. For example, the greater the temporal distance to the time period being imagined, the less detail or 'pre-experiencing' of that event that is reported [17]. The ability to imagine the future varies between individuals and is considered to be an important component of executive functioning related to activity in the prefrontal cortex [18].

Most reports of delay discounting applied to obesity have cited Mazur's original paper to justify using the single parameter hyperbolic model [16], in which the model provided the best fit to data. However, Mazur examined discounting behaviour in rats, over very short delays (usually seconds or minutes), and the question arises of whether it is a suitable model for describing human discounting behaviour over longer delay periods.

A number of psychological theories support a dual-process account of the ability to inhibit impulsive responses in favour of long-term gain [19]. Koffarnus and colleagues [20] reviewed delay discounting research in different impulsive populations, exploring the plausibility of a 'Competing Neurobehavioural Decision Systems' (CNDS) explanation of inter-temporal choice. The authors suggest that behaviours related to a reduced ability to delay rewards (including drug use, gambling and over eating) may be the result of a common underlying trait predisposing a person to choose immediate rewards over long term benefits. They discuss evidence favouring a role for two neural systems in trans-disease choice behaviour: an executive decision system correlating with lateral pre-frontal cortex (PFC) activation; and an impulsive system correlating with limbic reward activity. The CNDS model predicts that individual differences in one or both of these systems, determines choice behaviour. For example, it has been reported that that obese women gained more weight over the subsequent year if they showed reduced activation in brain areas associated with executive function when completing difficult discounting trials, compared to easy trials [21]. This supports the idea that sub-optimal functioning of executive areas leads to reduced self-control and overeating behaviour. However, it has been found that a 'dual-hit' of reduced executive control *and* increased desire for food cues reflected in nucleus accumbens (NAcc) reactivity, determined a vulnerability to over eating and higher BMI [22]. Hence, outcome behaviour in the delay discounting task may relate to activity in the reward system *and* the executive system. In support of this idea, Lopez et al [23] reported that NAcc activity in response to food cues predicted subsequent food desire and consumption over a week long period, but this was moderated by inferior frontal gyrus activity in a self-control task. Reward sensitive individuals displaying greater activity in this frontal region at baseline were more able to resist strong food temptations than those who showed lower activity. This evidence supports a dual-process approach to overeating and obesity [24].Consistent with this, neuroscientific evidence indicates that discounting is sensitive to two separate considerations – time delay and reward magnitude, corresponding to PFC and Ventral Striatum (in particular NAcc) activity respectively [25-27]. Thus the one parameter hyperbolic model may not be as appropriate as a dual-parameter model, which is more in line with obesity related empirical research evidence and neuropsychological theory.

In behavioural economics and addiction research, two-parameter models have been applied to discounting data and compared favourably to single parameter models [28-30]. For example, McKercher and colleagues [28] showed that in a general undergraduate student sample, two hyperboloid models fitted with an additional power function showed superior fit to discounting data compared to one parameter exponential and hyperbolic models. However, as both two-parameter models showed equally good fit to data, the authors advise that model selection should be based on theoretical, rather than just empirical reasons in any given population. A two-parameter model which has two parameters that distinguish between immediately available and delayed rewards is the βδ model [31]. However, Kable and Glimcher [32] have suggested that it is more likely that there is a single system underpinning desire for reward as soon as possible rather than a separate system for immediate versus delayed reward.

Therefore a novel two-parameter model that is consistent with evidence and theory is put forward. The saturating-hyperbolic model [33] is based on the premise that everyday decision making is difficult because decisions can result in rewards of different amounts at different timings. Within a delay discounting paradigm, the choice outcome behaviour is therefore dependent upon both temporal discounting and reward utility. This model has two free outcome parameters, *k* and Q, proposed to represent these processes respectively and is calculated using the equation:

$$\mathrm{V} = \mathrm{A} * \left(\frac{\mathrm{A}}{\mathrm{A} + \mathrm{Q}}\right) * \left(\frac{1}{1 + k\mathrm{d}}\right)$$

Where: V = Indifference Point (IP); A = Larger later reward; *k* = hyperbolic temporal discounting parameter; d = delay (days); Q = reward utility parameter.

The *k* parameter reflects the extent to which an individual discounts rewards over time. This is identical to the single parameter hyperbolic function *k* and represents the relative steepness of discounting at proximal versus distal delays. It is theorised to represent the ability to imagine the future which relies on activity in executive decision systems [18]. The Q parameter is called the reward utility function. This is typically a nonlinear function with a sigmoid shape with a threshold and saturation point [33, 34]. It is hypothesised to represent impulsive needs and desires, with variation in Q values indicating variation in nonlinear valuation [33]. A larger Q value indicates a shallow reward utility curve and signals that the reward is less appealing, whereas a smaller Q value indicates a steep reward curve and signals that the reward is more appealing. When combined with the hyperbolic function *k*, the Q parameter reflects the overall utility of the reward after a delay. If the reward is desired as soon as possible then the Q value will be large, indicating that any delay very rapidly devalues the reward. Therefore, the curve becomes saturated by enhanced proximal reward utility and the value of Q describes the extent of this saturation. In descriptive terms this is seen as a 'flattening' of the discounting curve where there is an immediate drop in where the curve starts on the y-axis. The larger the Q value, the larger the 'drop' and therefore the greater the emphasis on receiving the reward immediately.

To sum up, Q is theorised as a related yet distinct process to *k*, where the *k* parameter is a measure of ‘temporal discounting’ and is theorised to represent the ability to imagine the future and the Q parameter is a measure of reward utility, theorised to represent the impulsive need and desire for reward. When combined into a single model, the Q value represents the utility of the rewards as a function of delay, with higher values representing an emphasis on receiving that reward as soon as possible. Therefore, Q affects the overall valuation of the delayed reward being examined, contrasting with the single parameter model which only considers the steepness of discounting across indifference points. The saturating-hyperbolic model was selected because 1) it is directly comparable with the commonly used (nested) one parameter hyperbolic model, and 2) it is consistent with dual-process theories and neuropsychological evidence emphasising the importance of separate executive and reward functions in determining delay discounting in obesity research [21-23].

Although there have been numerous studies of delay discounting in obesity research, the relative fit of a dual-parameter model in an adult sample with wide ranging BMI is yet to be tested. The aim of the current study was to apply the commonly used one-parameter hyperbolic and the theory consistent, two-parameter saturating-hyperbolic model to discounting data from a sample of males and females with a wide BMI and age range. We predicted that the two-parameter model would show superior fit to data, and that Q and *k* would be related but independent constructs. In addition, the parameters were compared across weight groups to assess if they were sensitive to differences in discounting behaviour between lean and overweight/obese participants. We also included self-report measures of hedonic response to palatable food (Power of Food Scale [35]), disinhibited and restrained eating (Dutch Eating Behaviour Questionnaire [36]), and perceived control over food intake (Yale Food Addiction Scale [37]) to describe the population in terms of eating behaviour dimensions.

2. Method

2.1 Participants:

One hundred and one participants were recruited from the student and staff population at Swansea University and from professional/administration staff working for the local authority via email and poster advertisement. A pre-screening questionnaire was administered to ensure an equal distribution of lean and overweight/obese participants. Delay discounting and self-report data were collected from each participant. After applying Johnson and Bickel's [38] algorithm for identifying non-systematic delay discounting responders, and the removal of one outlier (with an area under the curve greater than 2.5 standard deviations from the mean), data from seventy nine participants was included for analysis (for sample characteristics, see Table 1).

Written consent was obtained from all participants and consent and all study procedures were granted departmental ethical approval by the Swansea University, Department of Psychology Research Ethics Committee.

Table 1: Sample characteristics for the Lean and Overweight/obese groups.

Demographic Characteristics	Lean (BMI 18-24.9): Mean (Range (SD))	Overweight/Obese (BMI 25+): Mean (Range (SD))
N	41	38
Age (years)	26.76 (19-46(7.9))	30.11 (18-51(9.5))
Males (N)	9	16
Females (N)	32	22
BMI	21.6 (18.3-24.8(1.9))	29.6 (25.4-43.6(4.4))
PFS	2.86 (1.3-4.3(.9))	2.54 (1.3-4(.8))
YFAS	1.49 (0-4(1.1)	1.89(0-6(1.5))
DEBQext	3.25 (1.8-4.4(.66))	2.93 (1.7-3.9(.56))
DEBQem	2.65 (1-4.2(.76))	2.35 (1-4.8(.89))
DEBQrest	1.51 (1-2(.51))	1.5(1-2(.51))

BMI (Body Mass Index); PFS (Power of Food Scale); YFAS (Yale Food Addiction Scale); DEBQ (Dutch Eating Behvaiour Questionnaire) ext (External eating), em (Emotional eating), rest (Restrained eating).

2.1 Procedure:

Participants were invited to attend a study ostensibly investigating ‘mood and decision making’. Each participant completed the delay discounting task, followed by the Power of Food Scale [35], Dutch Eating Behaviour Questionnaire [36] and Yale Food addiction Scale [37]. Height and weight was recorded by the researcher using the SECA laboratory scales in order to calculate body mass index (BMI) using the standard formula (kg/m^2). Participants were then debriefed, thanked and assigned course credit if they were students or £5 if they were members of the community.

2.2 Measures

2.2.1 Delay discounting task: A computer-based monetary delay discounting task with nine delays ranging from one day to one year. The larger, later amount was constant at £100 and the smaller, sooner amount varied using a random adjusting procedure, until the indifference point (IP) was calculated (the point at which the participant became indifferent to receiving the reward now or later). The IP for each delay was plotted as an indicator of the subjective value of that reward at the given delay. The lower the value, the less willing a participant is to wait for the reward. The plotted IPs can then be used to calculate a given outcome measure for discounting behaviour. A detailed description of the task can be found in McHugh and Wood's original paper [1].

2.2.2 Power of food scale (PFS): The PFS (Short version) is a 15 item questionnaire measuring participants' appetite at three levels: when food is available, present and tasted. The scale has been shown to predict food craving [39] and intake [40] in previous studies and is included here as a general measure of appetite for palatable foods readily available in the environment. Cronbach's alpha for the original scale was reported as 0.91 [35]. For group means see Table 1.

2.2.3 Dutch Eating Behaviour Questionnaire (DEBQ): The DEBQ is a commonly used self-report measure with three sub-scales. The external eating and emotional eating sub-scales measure readiness to eat in response to external and emotional cues (disinhibited eating) and the dietary restraint sub-scale measures the extent to which a person restricts their food intake in order maintain/lose weight. The scale is commonly used and was included to allow cross-comparison of sample characteristics with related research. Cronbach's alpha for the original scales were reported as between 0.8-0.95 [36]. For group means see Table 1.

2.2.4 Yale Food Addiction Scale (YFAS): The YFAS is a 25 item self-report measure of 'food addiction'. It attempts to identify those who have truly lost control over their eating behaviour. Participants receive a continuous score relative to the number of addiction criteria that have been met (for example, use continues despite knowledge of adverse consequences) with a maximum score of seven. The scale was included here as recent research has shown it to be a direct predictor of BMI [41], and a mediator between general impulsivity and BMI

[42]. Good internal reliability for the original scale was reported as Kuber-Richardson α=0.86 [37]. For group means see Table 1.

3. Analysis:

The one-parameter hyperbolic model was applied to the data using a least squares procedure on Gnuplot open source software [43], to estimate a *k* value for each participant. The saturating-hyperbolic model was applied to the delay discounting data using both Excel solver and Gnuplot software. Both fit the two parameters simultaneously and produced identical values. As a result the Q and *k* values were considered to be reliable.

The R^2 value for both models was calculated for descriptive purposes. Although often reported, the use of R^2 as a unit of comparison is more appropriate for linear regression models and has been argued to have little meaning for non-linear models [38]. As a result, the Sum of Squared Residuals (SSR) for both models were calculated and used for comparison analysis. The SSR is equivalent to a chi-square (χ^2) measure of model fit, and reflects the total deviation of the response values from the fit to the response values. As with χ^2, goodness of fit is indicated by lower values reflecting a smaller random error component. Given that a two-parameter model will always be expected to have a superior fit to a single parameter model, a comparison method accounting for this difference is necessary. The two indices that account for the number of parameters in each model and employed here were: Reduced SSR (RSSR) and Root Mean Square (RMS) of RSSR. RSSR is calculated by dividing the SSR by the number of degrees of freedom in the model, and the RMS (RSSR) is simply the square root of this. The degrees of freedom were calculated by subtracting the number of parameters from the number of data points (in this case there were nine data points, one for each delay period). In each case lower values indicate a better fit. A significantly better fit can be determined using a χ^2 difference test, as the models are nested.

Bivariate correlations were used to test if the parameters represented related or distinct processes. All analyses were conducted using IBM SPSS 20.0 software. All effect sizes were calculated post hoc using G* Power3 software [44].

4. Results:

The single parameter (*k*), and two-parameter (Q and *k* (sat*k*)) curves were fit to data from each participant and to the mean indifference points for the lean and overweight/obese groups for descriptive purposes (see Figures 1 & 2 respectively). The saturating-hyperbolic shows a visually superior fit to data (especially at the shorter delay periods) and has a markedly improved R^2 value for both weight groups. However, for a valid comparison, the SSR, RSSR and RMS (RSSR) were calculated for both models for each participant. Table 2 shows the mean fit indices for each model, along with the χ^2 difference test results. The SSR, RSSR and RMS (RSSR) values are smaller for the saturating-hyperbolic model, and the difference test is significant, indicating a statistically superior fit to data.

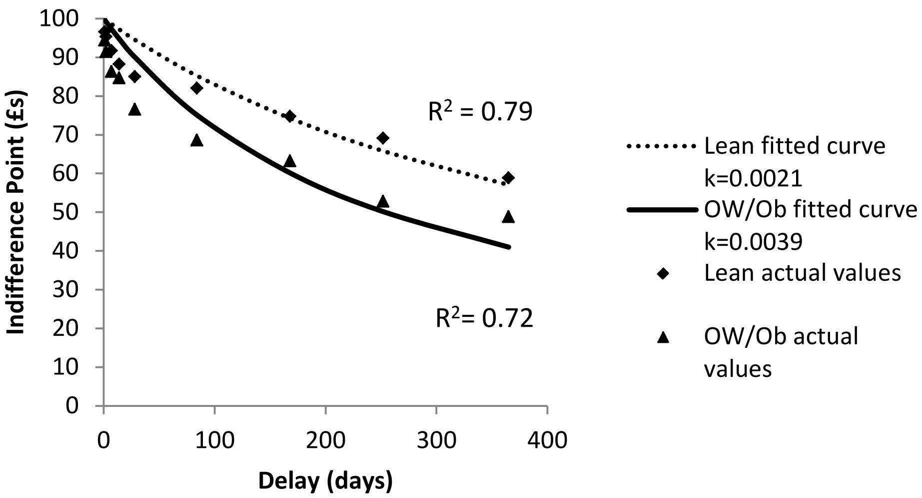

Figure 1: Graph to show the *k* values and one-parameter hyperbolic curves fitted to mean indifference points for lean and overweight/obese (Ow/Ob) participants (N=79).

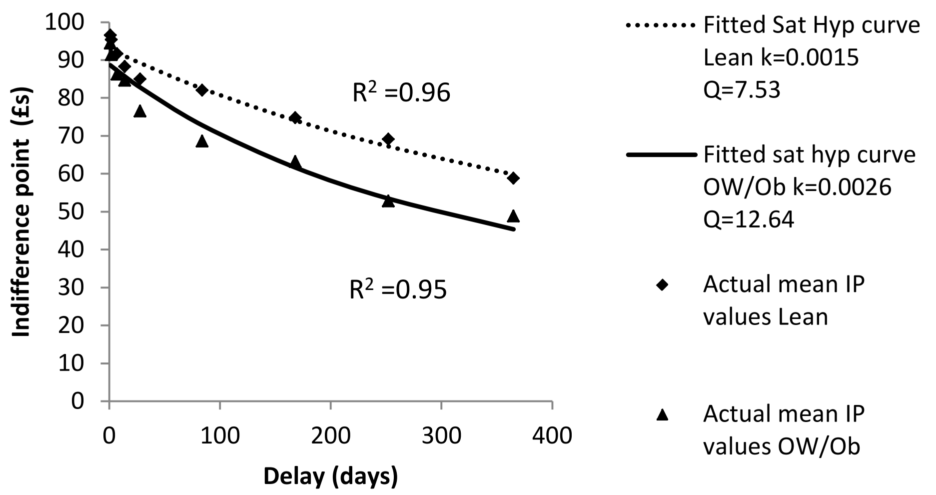

Figure 2: Graph to show the Q and sat*k* values and saturating-hyperbolic curves fitted to the mean indifference points for lean and overweight/obese (OW/Ob) participants (N=79).

Table 2: Mean (SD) values, for goodness of fit indices for the one-parameter hyperbolic model and the saturating-hyperbolic model.

Model/ Fit index	One parameter hyperbolic	Saturating-hyperbolic	X^2 Difference test (Df difference=1)
SSR	879.40 (1020.11)	528.24 (642.44)	351.16*
RSSR	109.93 (127.51)	75.46 (96.78)	
RMS (RSSR)	8.96 (5.48)	7.27 (4.77)	

SSR (Sum of Squared Residuals); RSSR (Reduced Sum of Square Residuals); RMS (RSSR) (Root Mean Square (RSSR)); Df (degrees of freedom); *p<0.0001. (ρ=0.35).

In order to explore the relationship between the two parameters Q and sat*k*, from the saturating-hyperbolic model, and the original *k* value from the one parameter model, they were entered into a bivariate correlation matrix (see Table 3). Results confirm that the *k* parameter in both models showed a near perfect correlation (r=.97). The Q parameter however, shows only a moderate correlation (r=.22) and so it is likely to represent a related yet distinct function.

Table 3: Spearmans correlation coefficients for the model parameters

	1	2	3
1. Q			
2. sat*k*	0.22*		
3. *k*	0.41**	0.97**	

Q (Saturating-hyperbolic model); sat*k* (Saturating-hyperbolic model); *k* (one-parameter hyperbolic model) *p<0.05 **p<0.01

The *k,* Q and sat*k* values were also compared across weight groups. The one parameter *k* values were significantly positively skewed (zskewness>1.96; p<.05) and so analysis was performed on log transformed data. ANOVA showed that the log*k* values were significantly higher for the overweight/obese group compared to the lean group (F(1,77)=8.016; p=.006; f=0.51). Demographic variables age and gender were compared across weight groups and although there were no significant differences (p>.05) there was a trend for the overweight/obese group to be older and include more males (p<.10). Therefore, the comparison was also run using ANCOVA, controlling for age and gender, however the outcomes did not change significantly. The overweight/obese group still showed significantly higher discounting rates than the lean group (F(1,75)=7.09; p=.009).

As a result of the significantly skewed nature of the sat*k* and Q values, and the fact that log transformation did not correct this, non-parametric tests were applied to the data. The Mann-Whitney U test of independent samples showed that the overweight/obese sample (N=38) had significantly (t=2.25; p=.025; d=0.8) higher sat*k* values (M=0.0042; SD=0.004) than the lean sample (N=41; M=0.0032; SD=0.004), as found with the original one parameter model. This is interpreted as particularly robust as the populations do not represent top and bottom quartiles, but a separation of those with a BMI below 25 and those with a BMI of 25 and above. There was also a significant difference between the weight groups for Q values (t=2.23; p=.026; d=0.8), where the overweight/obese group showed significantly greater Q values (M=12.8; SD=16.7) than the lean group (M=5.4; SD=6.1). For consistency, the raw *k* values from the single parameter model were also compared using the Mann-Whitney U test, and were once again significant (t=2.82, p=.005, d=.9), with the overweight/obese group displaying higher *k* values (M=.01; SD=.02) than the lean group (M=.005; SD=.01).

5. Discussion

Delay discounting has been related to obesity and has typically been modelled using a single hyperbolic parameter (*k*) representing the relative steepness of temporal discounting. However, neuropsychological research supports a dual-process account of discounting behaviour. The saturating-hyperbolic model has two parameters, sat*k* and Q, which are related but distinct indices proposed to represent temporal discounting and reward utility respectively. The model was therefore deemed consistent with the neuropsychological evidence and theory. The model was applied to discounting data from a sample with a wide range of BMIs and compared to the original single-parameter hyperbolic model. The new model showed a superior ‘goodness of fit’ to current discounting data and has therefore been shown to be a more accurate model of discounting behaviour in the current population.

The almost perfect correlation between the one parameter *k* value and the sat*k* value indicates that both parameters are measuring the same process and are therefore directly comparable. The more modest correlations between *k* and Q indicate that Q is measuring a related but distinct process to *k*. The parameters from both models were shown to be significantly higher in overweight/obese versus lean participants. This supports previous findings using the single parameter model, that delay discounting is an important component of obesity [3,4,6,7,8,10,11], but shows for the first time that the saturating-hyperbolic model is not only a better fit to data but maintains sensitivity to these differences. It is therefore a valid model for future use in obesity research. Indeed, very recently, Franck and colleagues [45] published a paper indicating that different models of discounting may best describe different populations and provide a tool for allowing different models to be compared. The saturating-hyperbolic model was not included in Franck and colleagues'[45] paper and would make a useful addition if applied to obesity research.

The CNDS model of delay discounting maintains that poor choices like over eating are the result of a high impulsive reward system, low executive system functioning or a combination of both. In the current sample, the overweight/obese group had significantly higher sat*k* and Q parameter values on the discounting task and it is theorised that the parameters may represent functioning of the executive and impulsive reward systems respectively. This is consistent with findings that it is the 'dual hit' of (food) reward desire and poor executive control that leads to over eating [22]. The saturating-hyperbolic model proposes that the two parameters represent temporal discounting (sat*k*) and reward utility (Q) which is consistent with neuropsychological research showing that delay discounting involves two related yet distinct processes [26]. The use of the saturating-hyperbolic model to measure these processes separately using the discounting task would be of great advantage in more precisely elucidating the factors that contribute to overeating. However, it would be informative to investigate the specific nature of the underlying processes by testing convergent validity of sat*k* and Q with neural responsivity in pre-frontal and reward areas and with measures of executive function and reward utility.

Carr et al. [50] coined the term 'reinforcement pathology' to describe the extent to which food is a reinforcer but also the degree of impulse control a person has. A strong motivation for food, measured using the Relative Reinforcement Value (RRV) of food task, has been shown to predict BMI and intake particularly in those who discount the future more steeply

[12, 51]. This suggests that food responsiveness is an important contributor to overeating in those with poor impulse control [49].. Research has also shown the discounting of food to be steeper in overweight/obese groups [13, 47] and so it would now be useful to apply the saturating-hyperbolic to food-related discounting behaviour. Findings from such research would allow us to begin to assess the relative influence of a general, trans-disease tendency to discount the future and a food specific tendency to discount the future in relation to overeating and obesity.

A few limitations are notable. Firstly, socio-economic indicators (income, IQ and education) were not recorded, but have previously been shown to be related to discounting behaviour [4, 53]. However, the majority of participants were recruited from the university student and staff population or local authority professional employees. Significant socio-economic-status (SES) differences between the weight groups were deemed unlikely. Future studies would benefit from a valid measure of SES in this context and from extending the sample to include a wider SES range (especially given the association between SES and obesity). Secondly, the sample was quite small for cross-sectional research however the predicted effects for Q and *k* emerged nonetheless, suggesting a robust finding. Future studies may benefit from a larger, more representative cohort. Lastly, the (sat) *k* parameter has been theorised to be representative of the ability to imagine the future and that this is an important aspect of executive control. But the fact that pigeons demonstrate hyperbolic discounting behaviour [57] and that dopaminergic activation of the reward circuitry also decreases in hyperbolic proportion to reward delay length in rhesus monkeys [59], suggests that other mechanisms may be responsible for discounting behaviour. However, human evidence showing that episodic future thinking (EFT) reduces *k* values [58], supports the idea that the ability to imagine the future might be one factor that underlies *k*, in humans at least.

As discounting is mutable under certain circumstances [54], it is a viable target for weight loss intervention research. Application of the two-parameter model could expand our understanding of exactly how an intervention exerts its influence. Recently, it was found that EFT reduces both discounting behaviour and food intake in lean and obese individuals [55, 56], presumably through enhancing the valence of future time periods and making discounting of the future less likely. Application of the saturating-hyperbolic to such data would further inform us of whether EFT is enhancing executive consideration of the future (sat*k*), reducing immediate reward utility (Q) or both? Application of this model in future research may enhance our understanding of which system underlies over eating in different individuals and contribute towards behavioural interventions that can be targeted effectively.

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