Decision-making, sensitivity to reward, and attrition in weight-management

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Running head:

Weight-management: decision, reward, and attrition

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What is already known about this subject

- In the treatment of obesity and overweight, research has shown that completion of weight-management programs is positively correlated with weight loss.
- Nonetheless, attrition is a common problem in such programs.
- Although correlates of attrition are often reported in the literature, theory-driven explanations are scarce.

What this study adds

- We propose an explanation that draws upon neuropsychological knowledge on reward-sensitivity in obesity and overeating to predict attrition.
- We tested the hypothesis on a sample of participants in a weight-management program, using a complex decision-making task and a quantitative model.
- Findings link attrition in weight-management to the neural mechanisms associated with reward-seeking and related influences on decision-making.

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Objective. Attrition is a common problem in weight-management. Understanding the risk factors for attrition should enhance professionals' ability to increase completion rates and improve health outcomes for more individuals. We propose a model that draws upon neuropsychological knowledge on reward-sensitivity in obesity and overeating to predict attrition.

Design & Method. 52 adults enrolled in a weight-management program completed a complex decision-making task. Individual decision-making characteristics – including sensitivity to reward – were further estimated using a quantitative model. Measures of impulsivity and risk-taking were also administered.

Results. Consistent with the hypothesis that sensitivity to reward predicted attrition, program dropouts had higher sensitivity to reward than completers ($p < 0.5$). No differences were observed between completers and dropouts in initial BMI, age, employment status, or the number of prior weight-loss attempts. Completers had a slightly higher education level than dropouts, but its inclusion in the model did not increase predictive power. Impulsivity, delay of gratification, and risk-taking did not predict attrition, either.

Conclusions. Findings link attrition in weight-management to the neural mechanisms associated with reward-seeking and related influences on decision-making. Individual differences in the magnitude of response elicited by rewards may account for the relative difficulty experienced by dieters in adhering to treatment.

Many obese individuals participate in weight-management programs, which aim to help in changing eating habits and losing weight. These programs typically include regular meetings with a therapist, nutritionist or other professional, in which participants receive information about healthy nutrition and lifestyle and discuss their goals and difficulties. A wide variety of programs are available: individual or group-based, with or without a structured diet, in medical, commercial, or other settings [1]. Research has shown that program completion is positively correlated with weight loss [2, 3]. Yet, attrition is a common problem. A recent review reveals attrition rates of 15%-59% (32% on average) in programs that last 10-16 weeks [4]. Attrition rates typically increase as the program gets longer (e.g., [3]).

Understanding the factors that contribute to attrition is important in order to improve completion rates and health outcomes for more individuals. Most studies of weight-management outcomes report attrition rates, and many of these studies also report correlates of attrition. However, these correlates tend to utilize routinely collected information, such as age, gender, and dieting history, rather than theory-driven variables [4]. Commonly reported predictors are younger age (e.g., [5]), female gender (e.g., [2]), lower education level (e.g., [6]), and more previous weight-loss attempts (e.g., [7]). Some studies have looked at psychological factors, such as high weight-loss expectations [7], low body image [8, 7], or personality traits [9, 10]. As has been pointed out [4], no consistent set of predictors has yet been identified.

The model we propose for explaining attrition in weight-management draws on the similarity between obesity and addiction, which has been pointed out by several researchers (e.g., [11, 12]). Some neural models have proposed that addictive behaviors involve an imbalance between two separate, but interacting neural systems [13, 14, 15, 16, 17]. The first is a motivational system, mainly amygdala/striatum dependent, which promotes reward-driven behaviors [18]. The second is a reflective system, mainly prefrontal-cortex dependent, which modulates deliberation, forecasting of future consequences, and inhibitory control [14, 15, 16]. Furthermore, earlier work has established that the motivation to seek un-sensed rewards (e.g., drugs) and sensed, natural rewards (e.g., food) involves common neural mechanisms, specifically dopaminergic ones [19]. More recent work has argued that this same neural substance – dopamine – may serve as a common currency for rewards, including food rewards [20]. From this perspective, overeating can be seen as a motivated behavior mediated by neural mechanisms similar to those studied in the field of addiction, and it may result from maladaptive performance in any of the two systems, i.e., an overactive motivational system or an underactive reflective system.

The notion that obesity is associated with an overactive motivational system has been supported by several empirical studies, which report a link between obesity and high sensitivity to reward (e.g., [21, 22]). With respect to the reflective system, studies have shown that interventions to boost reflective processes can help against overeating. For instance, increasing individuals' awareness to hunger has been found to improve control over eating decisions [23]. Other models include enhancing mindfulness [24], thoughtful attention [25], and recollection of recent eating [26].

In the present study we propose that the two-system model, which explains the dynamics of decision-making that underlay overeating and obesity, is also useful in explaining attrition in weight-management. Previous research provides some indirect evidence that attrition in weight-management is associated with overactivation of the motivational system. The activity of the motivational system is manifested by reward-seeking or drive-gratifying behavior [13]. Similar constructs, namely, high monotony avoidance and low inhibition of aggression, were found to predict attrition in weight-management [10]. Furthermore, dropout rates are higher when monetary penalties for failing to meet weight-loss goals are introduced [27], a strategy that can be interpreted as exacerbating reward-driven behavioral tendencies.

The literature on predictors of attrition in weight-management provides little support for the notion that attrition might result from deficient reflective processes or self-control. One study [28] reports a negative correlation between attrition and stimulus control – the tendency to avoid stimuli that elicit problem behavior, and to seek stimuli that encourage the alternative behavior. In contrast, in another study [29], measures of self-constraint and difficulty to control eating were found to be unrelated to attrition in weight-management. Similar null effects have been reported for cognitive restraint at eating [7], and weight locus of control [8].

Based on these findings, it seems plausible that attrition is more associated with overactivation of the motivational system than with underactivation of the reflective system. Nonetheless, the previous studies used a considerable variety of methods and measures and – more importantly – they each considered variables that were associated with either the reflective system or the motivational system. Thus the relative contribution of the two systems has not been systematically assessed.

In the present study we apply a cognitive model that incorporates both the reflective and the motivational systems: The Expectancy-Valence model [30, 31, 32, 33]. This quantitative model predicts the next choice ahead in complex decision-making tasks. According to the model, choices made in such environments reflect individual differences in three components of the learning and decision process: (1) a motivational component indicating the subjective weight the individual assigns to gains versus losses; (2) a recency / learning-rate component indicating the degree of prominence given to recently-obtained information, compared to past experiences; and (3) a probabilistic component indicating how consistent the decision-maker is between learning and responding. Based on a trial-to-trial analysis of behavior during the task, the model estimates three individual parameters corresponding to these components, for each decision maker [30].

In the two-system model, the motivational system is an abstraction of neural processes associated mainly with the amygdala and striatum, and the reflective system is an abstraction of neural processes associated mainly with the prefrontal cortex [13]. Activation in the amygdala and striatum has been linked to the motivational component of the Expectancy-Valence model, which is referred to as the *sensitivity to reward* parameter [31, 33]. Other studies associated the prefrontal cortex to the *recency* parameter (e.g., [32]), thus connecting this parameter with the reflective system. Therefore, these two components of the Expectancy-Valence model – sensitivity to reward and recency – serve as behavioral measures of activation in the motivational and the reflective systems, respectively. In the present study we analyzed the decision-making characteristics of weight-management clients using the Expectancy-Valence model, and tested the extent to which sensitivity to reward and recency predict attrition.

We applied the Expectancy-Valence model to data collected using the Iowa Gambling Task [34], a complex task that has often been used in studies of decision-making impairments among drug addicts (e.g., [15]), patients with eating disorders (e.g., [35]), and obese individuals [36].

Past research has linked obesity with impulsivity (e.g., [37, 21]), and there is some evidence that impulsivity predicts attrition in weight-management [10]. Obesity has also been linked with elevated risk taking in decision-making [38]. To examine the potential of these constructs in predicting attrition, we included the corresponding measures in present study as well.

Method

Participants.

Fifty-two adults enrolled in a weight-management program serving the university community (80% female). The mean age in the sample was 44 years (S.D. = 12.6). The mean initial weight was 207.4 lbs (S.D. = 52.2), and mean initial Body Mass Index was 34.11 (S.D. = 7.06). Participants were paid $20 on average for participating in the lab session.

Procedure.

The weight-management program is 16 weeks long. Participants meet weekly with an occupational therapist and receive information about healthy diet and lifestyle, as well as personalized guidance. Height is measured in the beginning of the program, and weight is recorded weekly. Participants attended a lab session in the beginning of the program, in which they completed the decision-making tasks and questionnaires described hereinafter. Data about attendance and attrition were obtained after the final meeting of the program. The study was conducted in compliance with the Institutional Review Board.

Main Measures.

The Iowa Gambling Task [34]. A complex decision-making task, in which participants make repetitive choices between four decks of cards (displayed on a computer screen), with the goal of maximizing their earnings. Each card selection yields a gain, but occasionally losses occur too. Two of the decks are disadvantageous, in that they yield relatively high gains along with occasional losses that are even larger, resulting in a net loss. The two advantageous decks yield small gains combined with smaller losses, resulting in a net gain. High performance on the task depends on the subject's learning to prefer the advantageous decks, i.e., to select more from them than from the disadvantageous decks. The task had 100 trials. Task results were further analyzed using the Expectancy-Valence model [30].

The Expectancy-Valence model (EV; [30]). According to the model, choice in complex environment is based on subjective expectancies, which reflect not only the actual outcomes experienced, but also individual differences in three components of the learning and decision process:

(1) A motivational component indicating the subjective weight the individual assigns to gains versus losses. The *sensitivity to reward* parameter ranges between 0-1, and represents the relative weight assigned to gains (rewards) in the evaluation of alternatives.

(2) A learning-rate component indicating the degree of prominence given to recent outcomes, at the expense of relying on the full range of past experience. The *Recency* parameter ranges between 0-1, and represents (inversely) the tendency to take long-term considerations into account [32].

(3) A probabilistic component indicating how consistent the decision-maker is between learning and responding. The *Consistency* parameter ranges between 0-10 and represents the tendency to choose from the alternatives with the higher subjective expectancies, as opposed to making random selections.

Based on a trial-to-trial analysis of behavior in the decision task, the model extracts three individual parameters corresponding to these components, for each decision maker. For a more detailed explanation of the computation and estimation process, see Appendix A.

Additional Measures.

Simplified variant of the Iowa Gambling Task (SIGT; see [38]). This version of the task is a direct measure of risk taking tendencies. The advantageous decks produce a constant small gain, i.e., no risk. The disadvantageous decks produce either gains or losses, i.e., they entail considerable risk.

Barratt Impulsiveness Scale [39]. A self-report, 30-item questionnaire measuring impulsivity.

A delay of gratification task (see [38]). A behavioral measure of impulsivity. In this task, participants repeatedly choose between two unmarked buttons displayed on a computer monitor. Buttons yield a small payoff of 5 points in either 40% (low frequency) or 80% (high frequency) of the trials. The low-frequency button is available for pressing as soon as each trial begins, while the high-frequency button becomes available after a ten-second delay. In each trial the participant chooses whether to wait the ten seconds for better prospects of reward, or press the low-frequency button immediately and move on to the next trial faster.

Food-Specific Go/No Go Task [37]. A behavioral measure of impulsivity. In this task, a rapid stream of desserts' pictures or vegetables' pictures is displayed, and the participants need to react as quickly and accurately as possible by pressing a key in response to vegetables, but not desserts. The task measures the ability to withhold, or inhibit, dominant behavior.

The Raven Advanced Progressive Matrices Test, part 1. A brief measure of intelligence.

Demographic information questionnaire. Included items referring to gender, age, educational level etc., as well as dieting history.

Results

Of the 52 original participants, 34 (65%) completed the program, and 18 (35%) did not. This attrition rate is similar to other reports in the literature (e.g., [9, 2, 4, 7]). On average, completers attended 15.6 weekly meetings out of 16 (S.D.=0.7), and dropouts attended 6.3 meetings (S.D.=2.6). Table 1 provides the mean values obtained by each group – completers and dropouts – in the main variables of the study.

< Insert Table 1 here >

No significant differences were observed between completers and dropouts in the following variables: initial weight and BMI, age, employment status and number of weekly working hours (73% of the sample reported having a full time job; 38.9 weekly hours on average), or the number of prior weight-loss attempts (mean = 7.04; S.D. = 7.62). A marginally significant difference emerged in education level: While all participants had high-school education, 61% of dropouts versus 85% of completers had a college degree (fisher's exact test, $p = 0.082$).

In the Iowa Gambling Task, program dropouts made somewhat less advantageous choices (mean = 51%, S.D. = 23%) than completers (mean = 62%, S.D. = 19%), a difference that was marginally significant in a two-sample t-test ($t_{(50)} = 1.79$, $p = 0.08$). Program completers' level of advantageous choice increased during the task, from the first block of 20 trials (mean = 54%, S.D. = 18%) to the last (mean = 67%, S.D. = 30%). This difference was significant in a paired t-test ($t_{(33)} = -2.33$, $p = 0.03$), indicating that adequate learning had occurred during the task. In contrast, dropouts' level of advantageous choice did not change between the first (mean = 51%, S.D. = 21%) and the last (mean = 53%, S.D. = 18%) blocks of 20 trials ($t_{(17)} = -0.28$, $p = 0.76$).

The Expectancy-Valence model analysis helps to shed light on the origin of this difference in task performance. Both groups had positive estimates of model fit (completers: mean = 15.22, S.D. = 23.03; dropouts: mean = 9.19, S.D. = 21.5. For details about fit estimation, see Appendix A). Means and standard deviations of the three model parameters – Sensitivity to reward, Recency, and Consistency – are given in Table 1. As expected, sensitivity to reward was significantly higher in program dropouts than in completers ($t_{(50)} = -1.95$, $p = 0.029$, one sided; Cohen's $d = 0.57$, indicating a medium effect size). A logistic regression model for predicting program attrition was significant (Likelihood Ratio $\chi^2_{(1)} = 4.18$, $p = 0.041$; Max-rescaled R-Square = 0.107). The dependent variable was coded "1" for dropouts and "0" for completers. The regression coefficient of the predictor – Sensitivity to reward – was significant as well ($\chi^2_{(1)} = 3.20$, $p = 0.037$, one sided). These results indicate that attrition in weight-management is predicted by overactivation of the motivational system.

On the other hand, the Recency parameter scores were similar in both groups ($t_{(50)} = 0.05$, $p = 0.96$), and the regression model was insignificant (Likelihood Ratio $\chi^2_{(1)} = 0.003$, $p = 0.96$; Max-rescaled R-Square = 0.0001). Hence, we found no evidence that attrition is associated with underactivation of the reflective system.

Although the difference in education level between completers and dropouts was not significant, the importance of controlling for education level in studies of obesity and decision-making has been noted in past research (Davis el al, 2010; Koritzky et al., 2012). We hence added education level as a binary variable to the regression model (coded "1" for those participants who had an academic degree, "0" for those who did not). This model had improved fit (Likelihood Ratio $\chi^2_{(1)} = 6.85$, $p = 0.033$; Max-rescaled R-Square = 0.170), yet each coefficient only achieved marginal significance (Sensitivity to reward: $\chi^2_{(1)} = 2.55$, $p = 0.055$; education level: $\chi^2_{(1)} = 2.64$, $p = 0.052$).

We found no indication that impulsivity, risk-taking, or intelligence predicted attrition in the sample. A series of two-sample t-tests revealed no significant differences between program completers and dropouts in the Barratt Impulsiveness Scale, the delay of gratification task, the Food-Specific Go/No Go Task, the simplified variant of the Iowa Gambling Task, or the Raven Advanced Progressive Matrices Test.

Discussion

In line with the hypothesis that attrition in weight-management is associated with a highly active motivational system, dieters were more likely to drop out of the program as their sensitivity to reward increased. This finding links attrition in weight-management to the neural mechanisms associated with reward-seeking and related influences on decision-making [21, 22, 31, 12]. From a neuropsychological point of view, rewards trigger affective signals in the amygdala and related structures, and there are individual differences in the magnitude of the responses elicited by various rewards [20]. Individuals whose response to reward is stronger have more difficulty to withdraw from reward-gratifying behavior [13], which, in the present case, explains why they were more likely to drop out of a behavior-changing program.

Recency, or the tendency to give prominence to immediate outcomes over time-distant ones [30], did not seem to affect attrition in weight-management. This result is in line with previous research [8, 7, 29], implying that impaired activity of the reflective system is not a major factor in this context. Additionally, the integration of both findings reveals that the difference in IGT performance between program completers and dropouts is due to inflated weight placed on gains by the latter.

The current study presents a theoretically-grounded explanation of attrition, linking it to neuropsychological phenomena commonly found in addictive behavior [15]. In light of the numerous accounts of high reward sensitivity in obese individuals (e.g. [21, 22]), we propose that reward sensitivity plays a key role in the persistence of obesity, which exacerbates the difficulty to withdraw from drive-gratifying eating. Overweight and obese individuals, who do not share this property of the motivational system, may find it easier than their counterparts to adhere to a weight-management program.

High impulsivity is associated with obesity, particularly in women (e.g., [37]). Yet, we found no indication that impulsivity predicts dropping out of weight-management. One plausible explanation for this is that measures of impulsivity capture processes that occur outside of the motivational system, i.e., self-control or delay of gratification, rather than response to reward per se. An alternative explanation is that, though impulsivity may be linked with the motivational system, a sample comprised solely of obese individuals does not have enough variance in this property to make it a useful predictor of behavior. By contrast, the Expectancy-Valence model is sensitive to individual differences in decision-making style within clinical populations [31, 33, 15], which may account for the advantage it had in the present context.

Homogeneity in the sample may also explain why age, gender, or dieting history did not predict attrition in the present study. This is in contrast with previous studies [4], though similar null results have been reported by others for gender (e.g., [5]), age (e.g., [9]), and previous dieting attempts [40]. We observed a somewhat higher level of education among program completers, which is in line with previous findings [6].

A potential limitation of the study is lack of control for eating disorders, and particularly bulimia nervosa. Compared to healthy, normal-weight controls, patients with bulimia nervosa display high sensitivity to reward in the Expectancy-Valence model [31]. It is unclear whether this phenomenon is linked particularly with bulimic behavior, as it may be confounded by excessive weight, repeated dieting attempts, or difficulty to resist tempting foods. Looking separately at obese dieters with and without bulimic symptoms may be required to understand if the disorder moderates the relationship between reward sensitivity and attrition.

Understanding the risk factors for attrition in obesity treatment should enhance professionals' ability to increase completion rates and improve health outcomes for more individuals. The present results can inform the development of strategies and methods that will counteract excessive reward seeking in the context of weight-management. Two potential avenues for this are plausible. First, strengthening the opposing processes, i.e., the reflective system: This may be achieved by certain forms of training [23, 26, 24, 25]. Second, intervening in the dynamics within the motivational system. This avenue has not yet been sufficiently researched, although existing theory and findings suggest its potential. While the brain may be exposed to different types of rewards (e.g., food, money, specific substances), it converts all rewards to a "common currency" in the form of dopamine levels [13, 20]. This implies that increasing the rewarding value of a behavior would increase the likelihood of choosing to engage in it. The provision of financial incentives for a behavior can be seen as an attempt in this direction, although the preferred incentive structure is difficult to determine [27]. Future research may benefit from investigating this notion further.

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Appendix (supplementary material)

Cognitive modeling of the task's results.

We employed the revised Expectancy Valence model (rEV; Busemeyer & Stout, 2002; Yechiam & Ert, 2007), a learning model predicting the next choice ahead in repeated decision-making. The model assumes that making repeated choices from a set of alternatives generates a process of learning the expectancies of these alternatives. The individual's choice is based on subjective expectancies, namely, an incorporation of the actual experienced outcomes into a learning and decision process with three components. Each component is represented by a parameter:

1) Relative weight to gains and losses, measured by the attention-weight parameter. The subjective evaluation of the gains and/or losses obtained upon making a choice is called a valence, and denoted $v(t)$. It is calculated as a weighted average of the gains and losses resulting from the chosen option in each trial t.

$$v_j\,(t) = w \cdot win(t) \; - \; (1\text{-}\, w) \cdot loss(t) \; ,$$

where $win(t)$ and $loss(t)$ are the amounts of money won or lost on trial t; and w is the attention weight parameter ($0 \leq w \leq 1$).

2) The rate at which recent outcomes are updated, or the relative effect of recent outcomes on the subjective expectancies formed by the decision maker. This is measured by the recency parameter. The outcomes produced by each alternative j are summarized by an expectancy score, denoted $E_j\,(t)$, and updated as follows:

$$E_j(t) = E_j(t\text{-}1) + \phi\,[v(t) - E_j(t\text{-}1)] \; ,$$

where j is the selected alternative. The recency parameter, ϕ, describes the degree to which subjective expectancies reflect the influence of the most recent experience relative to more distant past experiences ($0 \leq \phi \leq 1$). Higher values of ϕ indicate a greater effect of recent information (at the expense of relying on the full past experience) on the next decision made. Low values of ϕ are generally more optimal.

3) The effect of expectancies on further choice, measured by the choice consistency parameter. The probability of choosing an alternative is a strength ratio of the subjective expectancy of that alternative, relative to all choice options (using Luce's rule):

$$\Pr[G_j(t+1)] = \frac{e^{\theta(t)\cdot E_j(t)}}{\sum_j e^{\theta(t)\cdot E_j(t)}} \ ,$$

where $\Pr[G_j(t)]$ is the probability that alternative j will be selected on trial t. The term $\theta(t)$ controls the consistency of the choice probabilities and the expectancies, where: $\theta(t) = c^5 - 1$, and c is the choice consistency parameter ($0 \leq c \leq 10$). Higher values of c reflect higher consistency.

Parameters are estimated based on a trial-to-trial analysis of the decision maker's behavior in the task. The accuracy of the model is assessed by comparing its ability to predict the individual's next decision, to a prediction based on the respondent's mean choices (a baseline model). The estimation procedure is described in detail in Busmeyer and Stout (2002). The statistical test used for comparing the fit of the models is the Bayesian Information Criterion (BIC) for log likelihood differences. Positive values of the BIC statistic indicate that the cognitive model performs better than the baseline model.

Table 1. Means (SD) of main study variables in program completers and dropouts

	Completers	Dropouts	
	n=34	***n=18***	
% women	82%	78%	
Sensitivity to reward	0.57	0.72	*
	(0.30)	(0.22)	
Recency	0.25	0.25	
	(0.37)	(0.36)	
Consistency	3.28	3.57	
	(3.18)	(1.68)	

* $p < 0.05$