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Setting up smARt weight loss goals

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Abstract

The present paper proposes the creation of customized programs and policy interventions that target individuals with specific health characteristics in order to set Achievable and Realistic goals. Using economic and biometric tools, we investigate whether inducing health-related thoughts influences the behavior of normal weight, overweight, and obese individuals. Specifically, we analyze the effects of inducing thoughts about the benefits of dieting and exercising along with the effects from exposing individuals to different self-images in food choices, time preferences, and cognitive ability. The results show that the provision of information about the benefits of eating healthy and exercising had a positive impact on overweight and obese individuals. However, when the obese became more self-conscious about their image, the opposite effect was found. This effect is attributed to the possibility that obese individuals look at the reward of becoming healthier as somewhat farfetched or difficult to achieve.

Key words: Episodic prospection; Health; Goal Setting; Obesity; Physical Activity; Self-consciousness

1. Introduction

It is commonly believed among economists and psychologists that an individual's sense – or lack thereof – of psychological connection with his future self plays a central role in shaping his decisions over time (Schelling 1984; Thaler and Shefrin 1981). Charles Dickens' story of Ebenezer Scrooge in *A Christmas Carol* serves as motivation for our work in the present paper. In the story, cruel Scrooge is given a chance to redeem himself through the intervention of ghosts from his past, present and future. The visits from ghosts of the past and present make him melancholic, but there is no change in behavior. It is not until he is visited by the Ghost of Christmas Yet-to-Come that he decided to change his present behavior. As the story points out:

> *"Ghost of the Future!" exclaimed Scrooge, "I fear you more than any spectre I have seen. But as I know your purpose is to do me good, and as I hope to live to be another man from what I was, I am prepared to bear you company, and do it with a thankful heart. Will you not speak to me?"*
>
> *Charles Dickens (1843)*

Related to this story is the notion that the degree of connectedness of an individual with his self-image and future self might affect his decision-making processes, since a future self might present challenges to his imagination. For example, researchers believe in the existence of a gap or misunderstanding between how an individual will feel in the future about decisions taken in the present (Loewenstein, O'Donoghue, and Rabin 2003). Loewenstein (1996) argues that a more vivid visual imagery about future actions might amplify the emotions related to the processing of those actions. These heightened emotions might help increase the salience of future consequences of a present decision. For instance, the extensive experience nutritionists have with issues such as obesity and diabetes acts to charge their emotions against those problems, which in turn drives them towards healthier diets (Wardle, Parmenter, and Waller 2000).

Recently, researchers have taken interest in investigating the relationship between evoking future event simulation and the response of memory processes and behavior. In these studies, participants are typically instructed to imagine realistic events in their future, after which they are asked to make decisions under certain scenarios (Carvalho, Meier, and Wang 2016). For example, in a study conducted by Mani et al. (2013), subjects were induced to think about a hypothetical financial hardship situation. The authors found that inducing thoughts about finances significantly decreased the cognitive capacity of the poor, but it had no effect on wealthy participants. They attributed this effect to the depletion of mental resources of the poor, which according to them, reduced their resources available for other tasks. While this literature mainly focuses on financial problems, little has been done regarding health and food consumption. This study is the first to investigate the effects of inducing health-related thoughts on subsequent decisions in situations that require self-control exertion (i.e., eating healthy vs. unhealthy food). One issue that arises in the aforementioned literature is that individuals often fail to identify with their future selves due to lack of imagination (Parfit 1971; Schelling 1984), thus impairing the level of self-control they exert in subsequent decisions. In this regard, Hershfield et al. (2011) proposed that allowing people to interact with age-progressed renderings of themselves caused them to allocate more resources into the future. On that basis, we presented subjects with digital images representing a "healthier" and an "unhealthier" version of themselves in order to facilitate "reward" self-imagination and assess self-control. Moreover, we examined the effect of inducing thoughts about dieting and exercising on cognitive performance, food choices, and time preference decisions for overweight, obese, and normal weight individuals. Biometric data, including eye-tracking and electroencephalogram (EEG), were utilized to aid in a more accurate and extensive analysis of the results.

Our findings highlight the importance of designing policy interventions that are tailored to the specific health characteristics of individuals for setting Achievable and Realistic goals. While the business terminology refers to smart goals as being specific, measurable, achievable, realistic, and time-bound, we focus on the Achievable and Realistic concepts since we consider these two characteristics to be the most influential and difficult to attain by overweight and obese individuals. We show that while providing information about the benefits of exercising and eating healthy had a positive influence on overweight and obese individuals, long-term goals work poorly for the obese, who might need more tangible short-run results.

The remainder of this paper is organized as follows. Section 2 describes the experimental setup and design. Section 3 discusses the main results, while Section 4 concludes. Appendix A provides the details of the experimental procedures.

2. Methodology

2.1. Experimental Design

The experiment consisted of a between-subject design in which participants were randomly assigned to one of three experimental conditions, where inducement of health-related thoughts was the manipulating factor: 1) *pure mental representation condition,* 2) *goal setting "episodic prospection" condition,* and 3) *control condition*. Specifically, subjects in the pure mental representation condition watched a 2-minute video, which induced them with thoughts related to the benefits of dieting and exercising. Subjects in the episodic prospection goal setting condition were exposed to digitally created pictures of themselves using a computer algorithm that modified their image by increasing and decreasing their weight. In this condition, subjects had the opportunity to react to their self-image and obtain the "reward" of being a healthy person (by either losing or maintaining their weight) and they were asked to remember their self-image representations throughout the experiment.[1] In the control condition, subjects received no information, and simply waited 2 minutes before starting the experiment.

2.2. Participants

The sample used in this study consists of 182 right-handed students (91 males and 91 females) from a large university in the Southern U.S. Participants were recruited using bulk emails and received a show-up compensation fee of $20 for participating in the experiment. In addition, an incentivized time preference elicitation mechanism described below provided the opportunity for subjects to earn additional payments. To qualify for the study, subjects had to be at least 18 years old and must not have had a history of any psychiatric or eating disorders. Moreover, subjects were required to fast for three hours prior to the experiment. The data were collected over the period from July to September 2016 and the study was approved by the Institutional Review Board.

2.3. Experimental Procedures

Upon arriving to the lab, the participant received a unique identification number and signed a written informed consent. EEG electrodes were then attached to the subject's scalp and he was seated on a chair in front of a computer with a Tobii TX 300 eye-tracking device. The sessions lasted around 60 minutes.

Each session consisted of three tasks. It included a cognitive performance task, a food choice task, and a time preference task (in randomized order). The cognitive performance task included

[1] Subjects in the second condition were shown two digitally modified images of themselves with higher and lower weight, using a computer algorithm available at: http://www0.modiface.com/weightmirror/. The image was modified about 15% with respect to the current BMI; the proportional change was mild in order to represent realistic goals. Moreover, the order in which the two images were presented was randomized across subjects.

24 problems from the Raven's Progressive Matrices test, which is a computer-based test commonly used to measure fluid intelligence (cognitive function) independent of acquired knowledge (Raven 1991). The food choice task presented subjects with 20 trials, each consisting of a fixation point shown for 2 seconds (s), followed by a stimulus (food product image) (8s), a choice decision, and an inter-stimulus (0.75s). For each decision, subjects were asked to choose between a healthy and an unhealthy version of the same snack (e.g. original vs. light Yoplait vanilla yogurt). The healthy and unhealthy snacks were selected to be similar in every aspect, except the number of calories (they were similar in terms of price, brand, packaging and flavor) (Figure A1 in Appendix A). The 40 products used were the actual images taken from Walmart's website and they were all ready-to-eat items. The list of the products used in this task is available in Appendix B. In order to incentivize the food choice task, one of the twenty decisions was randomly chosen at the end of the session and subjects had to eat the product they chose before being paid and leaving the laboratory. The binding decision was determined using a bingo cage that contained 20 balls numbered 1-20. At the end of the experiment, subjects drew a ball from the bingo cage to determine the binding decision. Lastly, the time preference task consisted of a Multiple Price List (MPL) design, which is widely used to elicit time preferences in economic experiments (Andersen et al., 2008; Andreoni and Sprenger 2012; Andreoni et al., 2015; Hardisty et al., 2013). The task consisted of 15 binary choices, in each of which participants were required to choose between a lower immediate payment and a higher delayed payment to be received two weeks later (Appendix C). In order to incentivize the time preference task, one of the choices was randomly selected using a bingo cage and subjects had a 10% chance of being paid. If the immediate reward was selected, the amount was added to the $20 participation fee and the subject received the total payment at the end of the session. If a delayed reward was selected, the reward

amount was directly deposited to the subject's bank account after the specified number of days had elapsed in order to minimize transaction costs. For delayed payments, we used the SurePay service from WellsFargo Bank, which only requires the email of the participant to make the deposit. A pilot test with 15 individuals confirmed the deposit at the specified date.

After the completing the three tasks, participants filled out a survey regarding their demographic and behavioral characteristics. Since participants were required to fast for three hours prior to the experiment, they were asked to report the time at which they consumed their last meal before arriving to the experiment. Moreover, participants self-reported on a scale from 1 to 9 (1 = Not at all, and 9 = Extremely) how hungry they were at the beginning of the session. Finally, the EEG electrodes were removed and the actual weight and height of each participant were collected using a calibrated digital scale and measuring tape, respectively. The body mass index (BMI) was calculated as weight in kilograms divided by height in meters squared, and it was used to classify subjects as either normal weight, overweight, or obese (WHO 2000).[2]

2.4 Data Collection and Reduction

While subjects performed the tasks, their brain activity was measured using an electroencephalogram. Specifically, electrodes were used to record brain activity from nine different scalp sites including prefrontal (F3, F4, FZ), central (C3, C4, CZ), and parietal (P3, P4, PZ) cortices. Electrode impedances were reduced to less than 20Ω and a 0.5-Hz-high-pass and 45-Hz- low-pass filters were applied. The data collection was conducted in iMotions software, and all EEG signals were collected at a sampling rate of 256 Hz. After the recordings, the EEG data were segmented into 20 epochs, one for each food choice decision. Each epoch lasted 2.5 seconds, 0.5

[2] BMI has been universally used to measure fatness since the information needed to calculate it is easy to collect and relatively common in social science datasets (Burkhauser and Cawley 2008). However, more accurate measures of fatness can be used including total body fat, percent body fat, waist circumference, and waist-to-hip ratio (Freedman and Perry 2000).

seconds before stimulus onset and 2 seconds after stimulus onset. Furthermore, subjects' eye movements were recorded using a Tobii TX300 eye tracking device, which was embedded in the computer and tracked gaze position using near-infrared technology at a sampling rate of 120 Hz.

3. Results

3.1. Descriptive Analysis

Individuals were classified according to their weight status using body mass index. According to the World Health Organization (WHO), normal weight is defined as a BMI between 18.5 and 24.9 kg/m^2, overweight is defined as a BMI between 25 and 29.9 kg/m^2, and obese is defined as a BMI of 30 kg/m^2 or more (WHO 2000). The average BMI of the sample was 24.7, which is indicative of normal-weight. This value is slightly lower than the average BMI of the population in the city where the study was conducted, which is 26.6 (city-data 2017). Of the total 182 participants, 116 were normal weight, 41 were overweight, and 25 subjects were obese. As shown in table 1, the distribution of weight status is balanced across treatments, with a larger number of normal weight individuals for all treatments.

Table 2 presents a description of the sample along with a balance check across treatments. Regarding behavioral characteristics, the results indicate that the between-subject treatments do not differ in terms of exercising, hunger levels, the presence of serious health issues, and the level of impatience. However, there is a significant difference in the cognitive function of the individuals across treatments. This difference along with the relationship between cognitive ability and weight status will be further addressed in the following section.

Table 1. Sample size by treatment and BMI category

	Normal	Overweight	Obese
Overall	116	41	25
Control	40	12	8
Pure Mental Representation	36	15	9
Episodic Prospection	40	14	8

Table 2. Balance test across treatment groups.

Variable	**Description**	**Mean** (Std. Err.) Control	**Mean** (Std. Err.) Pure Mental Representation	**Mean** (Std. Err.) Episodic Prospection	**Tests**
Cognitive score	Number of correct answers, 0-24	17.28 (3.02)	18.55 (3.61)	18.68 (2.72)	*p*-value= 0.02
Impatience	Number of impatient choices, 0-15	5.40 (3.90)	4.97 (4.39)	4.71 (4.61)	*p*-value=0.35
Exercise	Percentage of days per year exercised	40.04 (27.29)	40.97 (31.06)	52.54 (51.45)	*p*-value= 0.74
Smoke	DV = 1 if smoker, 0 otherwise	0.07 (0.25)	0.00 (0.00)	0.11 (0.32)	*p*-value= 0.03
Health issues	DV = 1 if had serious health issues, 0 otherwise	0.03 (0.18)	0.00 (0.00)	0.03 (0.18)	*p*-value= 0.36
Hungry	Hunger level, 1-9	0.53 (0.50)	0.58 (0.50)	0.66 (0.48)	*p*-value= 0.35
Male	DV = 1 if male, 0 otherwise	0.43 (0.50)	0.51 (0.50)	0.55 (0.50)	*p*-value= 0.44
White	DV = 1 if White, 0 otherwise	0.45 (0.50)	0.30 (0.46)	0.29 (0.46)	*p*-value= 0.12
Hispanic	DV = 1 if Hispanic, 0 otherwise	0.25 (0.44)	0.18 (0.39)	0.15 (0.36)	*p*-value= 0.33
Other	DV = 1 if race other than White or Hispanic, 0 otherwise	0.30 (0.46)	0.52 (0.50)	0.56 (0.50)	*p*-value= 0.01
N		60	60	62	

With respect to the socio-demographic characteristics, the results show that about half of the subjects in each condition were male and there was no difference in the proportion of White and Hispanic individuals across treatments. Yet, the balance test shows that there were significant differences in the proportion of subjects from other races. While 30% of the subjects identified themselves as non-White and non-Hispanic in the control, over 50% of the subjects in the treatments fell under this category.

In the food choice task, participants had to choose between a healthy and an unhealthy snack in 20 different choice sets. Recall that the food products where identical in every aspect, including brand, price, packaging and flavor, except for the number of calories. Figure 1 shows the relationship between BMI and healthy food choices by treatment. Overall, it is expected that providing information about the benefits of dieting and exercising and showing self-image representations evoking participant's imagination of their future selves would have a positive effect on the number of healthy products chosen by individuals. However, we found that the treatment effects vary depending on the weight status of the individual. The results show that in the control condition, the number of healthy choices is represented by a strictly decreasing function with respect to BMI; that is, individuals with higher BMI made less healthy choices. This result goes in line with Fan and Jin (2014) who found that overweight and obese individuals have poor eating habits (eat less fruits and vegetables and more saturated fats) compared to normal-weight individuals due to lower levels of self-control capacity.

After watching the health-related video in the *pure mental representation condition*, subjects with the highest BMI chose more healthy products, while normal weight individuals slightly decreased the number of healthy choices. This result suggest that inducing obese subjects with thoughts about dieting and exercising encourages them to choose healthier food. Interestingly, the opposite effect was found in the *episodic prospection condition*, where the number of healthy choices increased only for normal and overweight subjects and substantially decreased for obese subjects. A potential explanation for this result is that overweight individuals look at the goal of becoming healthier (by either gaining or losing weight) as something attainable in the short run;

however, obese people might not be as stimulated or excited about looking at their healthier selves since they perceive this goal to be out of reach or unattainable. This effect can also be explained by the discrepancy between weight-loss intentions and actual eating behavior found in obese individuals (Fan and Jin 2014). Although there is evidence that obese individuals have a much stronger intention to lose weight than normal-weight individuals (Fan and Jin 1013), their lack of self-control impedes their weight goal achievements (Fan and Jin 2014). Behavioral economists classify obese individuals with self-control problems as either naïve or sophisticated (O'Donoghue and Rabin 1999). The naïve category includes individuals who are not fully aware of their lack of self-control, and thus engage in unhealthy behavior one day with the promise to make up for it the next day. On the other hand, the sophisticated category describes individuals who understand their self-control issues, and thus, resort to commitment devices to enhance their likelihood of maintaining good behavior.

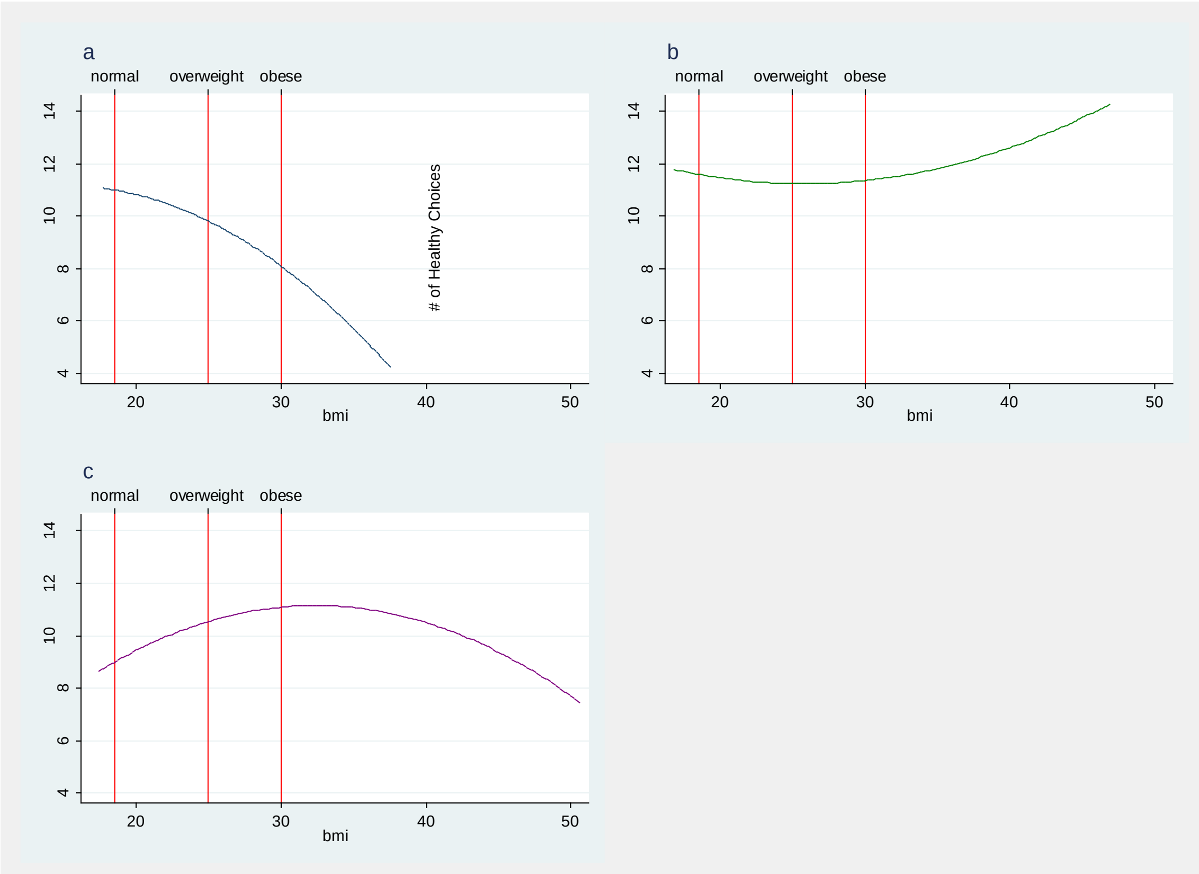

Figure 1. Number of healthy choices by BMI and treatment. a) Control; b) Pure mental representation condition; c) Episodic prospection condition.

The behavioral findings described above are further supported using the visual attention metrics obtained with eye-tracking. Specifically, the time (ms) subjects spent looking at each food alternative was used to measure the visual attention and appeal of each food product. It is hypothesized that the visual attention of subjects while observing the products will vary depending on their BMI. Overall, subjects in the *control* and *episodic prospection conditions* spent more time looking at the unhealthy alternative, while those in the *pure mental representation condition* spent more time looking at the healthy food snack (Figure 2). When looking at visual attention by treatment, we find that normal, overweight, and obese participants in the *control* spent more time looking at the unhealthy alternative. Their visual attention goes in line with their choices. Obese subjects in the *episodic prospection condition* spent more time looking at the unhealthy snack (3948 ms) than normal weight individuals (3806 ms), which might explain why they chose more unhealthy products in that treatment.

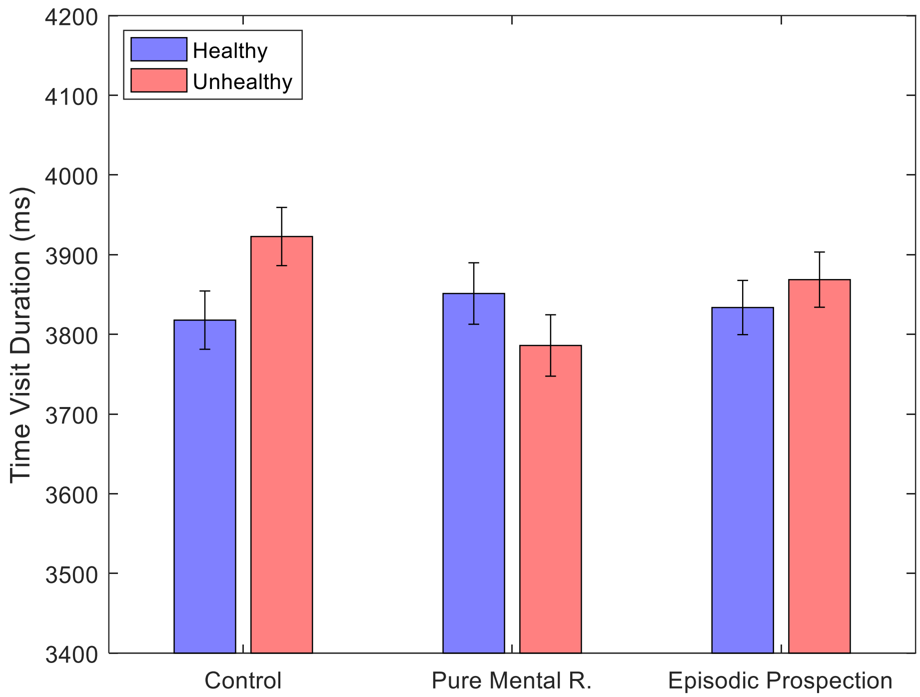

Figure 2. Time visit duration (ms) on food choice task by treatment.

Furthermore, we analyzed the relationship between levels of impatience and BMI by treatment (Figure 3). Previous experimental research find a positive relationship between BMI and impatience (Chabris et al., 2008; de Oliveira et al., 2016; Sutter et al., 2013) and our results are in line with these findings. That is, obese subjects displayed higher levels of impatience in both the *control* and *episodic prospection conditions*, while the opposite effect was found for obese individuals in the *pure mental representation condition*.

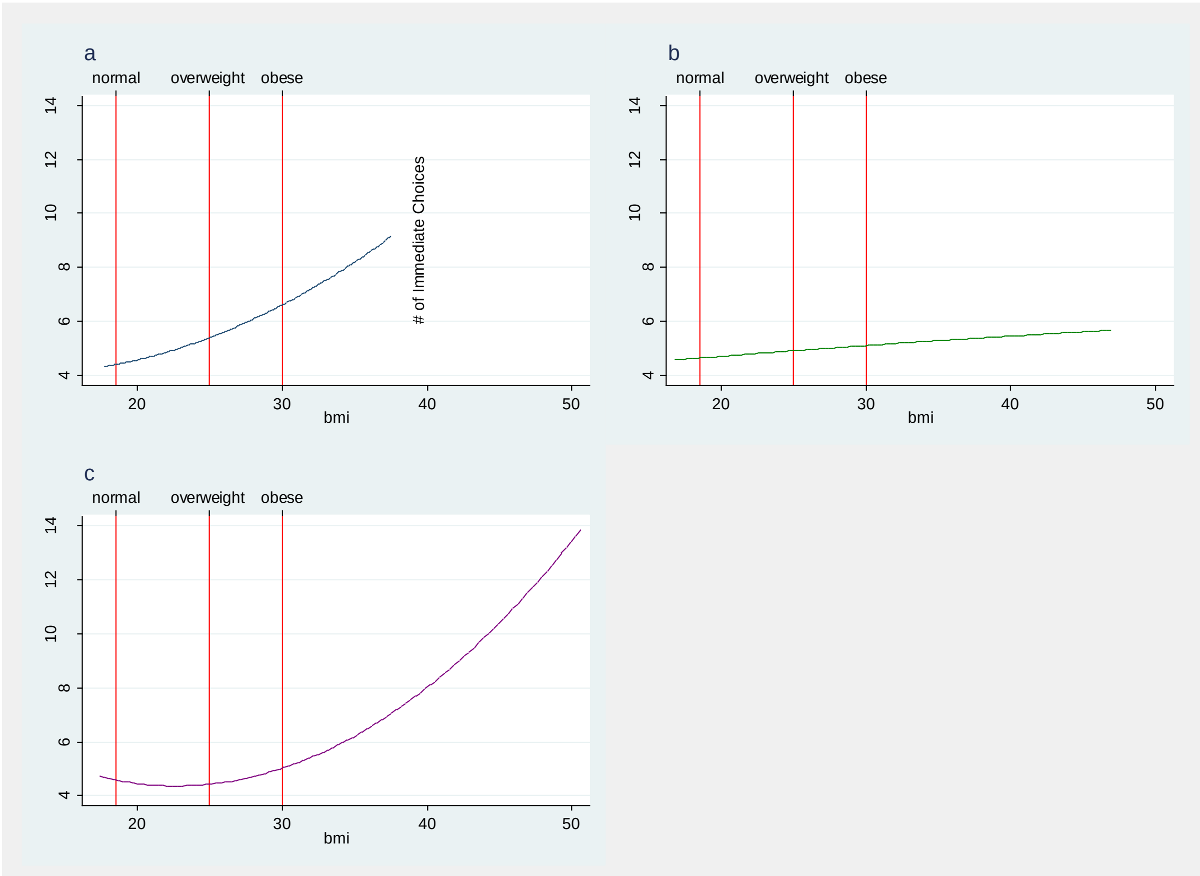

Figure 3. Number of immediate choices by BMI and treatment. a) Control; b) Pure mental representation condition; c) Episodic prospection condition.

In order to have a better understanding of the subjects' brain processing activity while making decisions, two metrics were calculated from the EEG data. The first metric corresponds to the brain engagement index, which is related to brain processes that require attention and visual scanning; therefore, this index increases with higher levels of attentiveness and focus. The second metric, referred to as brain workload, is used to describe executive processes including working memory, problem solving, and analytical reasoning. Thus, higher levels of this index are indicative of higher working memory load (Berka et al., 2007). The analytical approach used to estimate the engagement and workload indexes employs linear and quadratic logistic discriminant function analysis (DFA) to identify and quantify cognitive state changes using a combination of relative and absolute power spectra variables from 1-40 Hz. A detailed description of the computation of the engagement and workload classifiers can be found in Berka et al. (2007) and Johnson et al. (2011).

Figure 4 displays the brain engagement of participants while performing the food choice task. While there was no difference in the level of brain engagement for normal weight individuals across all conditions, overweight individuals showed significantly higher brain engagement after watching the health-related video. For obese subjects, brain engagement significantly decreased in the *episodic prospection condition* compared to the *control* and *mental representation conditions*. This indicates that after looking at the two self-image representations of themselves (higher weight and lower weight), obese individuals became less engaged in the task, thus being less meticulous about their food choices. The result was a higher tendency to choose unhealthy food products and becoming more impatient (i.e., choosing the immediate payment alternative more often).

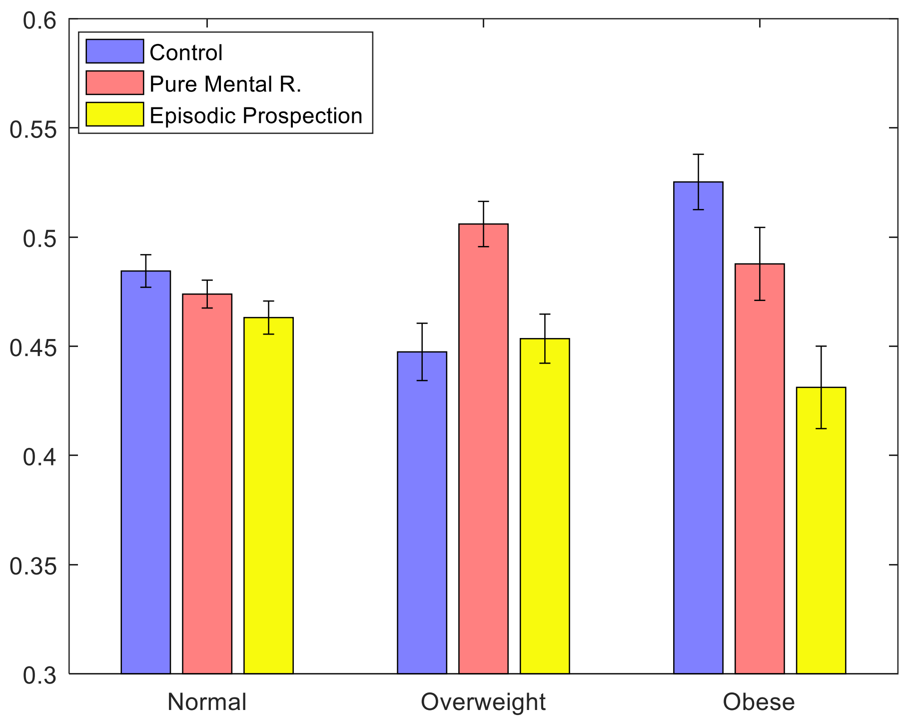

Figure 4. Subjects' brain engagement on food choice task by BMI and treatment.

Similarly, Figure 5 shows the average brain workload by BMI category and treatment. As shown in the literature, imposing cognitive taxes on individuals, such as evoking financial concerns, interpreting new rules, preparing for prolonged interviews, and responding to complex incentives, demands high levels of workload and impedes cognitive capacity (Mani et al. 2013). In this regard, it is expected that after being induced with health-related thoughts, participants' workload level would increase while performing subsequent tasks. The findings show a similar pattern in terms of workload levels across conditions and BMI categories. In particular, all subjects displayed significantly lower workload levels in the *control condition* compared to the other two conditions, with no differences in the brain workload between the *pure mental representation* and *episodic prospection conditions*. This indicates that the treatments were successful in having the desired effect on the level of workload subjects displayed regardless of their weight status.

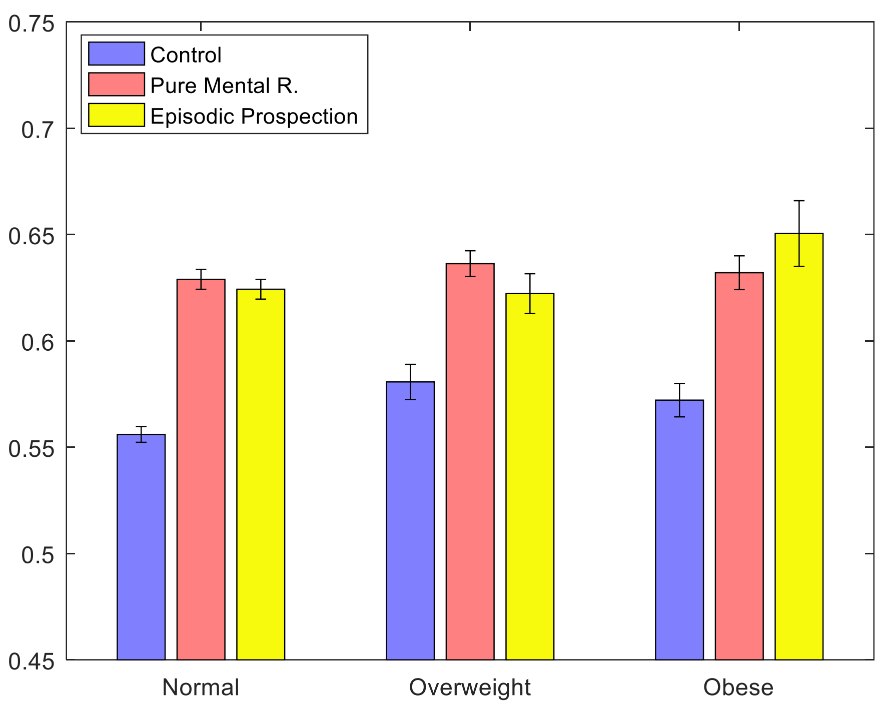

Figure 5. Subjects' average workload on food choice task by BMI and treatment.

3.2. Regression Analysis

Following Train (2009), we assume that decision maker n faces a choice among J alternatives in each of S choice tasks. The utility that the decision maker obtains from each alternative j, is represented by:

$$U_{njs} = V_{njs} + \varepsilon_{njs} \; \forall \; j \; . \tag{1}$$

where V_{njs} is a vector of explanatory variables, and ε_{njs} is an i.i.d error which follows a logistic distribution.

In the food choice task, subjects were asked to make twenty choices between two products differing only in the number of calories. Other than that, the products had identical attributes, hence there are no product specific covariates. The food choices were modeled as:

$$Y_{njs} = \beta_0 + \beta_1 Mental_i + \beta_2 Episodic_i + \beta_3 Weight_i + \beta_4 Interactions_i + \beta_5 X_i + \epsilon_i \tag{2}$$

where the dependent variable is an indicator variable of whether the individual chooses the healthy alternative. The variables $Mental_i$ and $Episodic_i$ are treatment dummies ($Control_i$ is the excluded category); $Weight_i$ is a categorical variable indicating whether the individual is normal-weight, overweight, or obese; X_i is a vector of socio-demographic and behavioral characteristics, and ε_i is an error term i.i.d logistic.

As shown in Table 3, the specification in column 1 included the two treatments as the only explanatory variables, while in column 2, the variables describing overweight and obese individuals along with interactions were also included. The specifications in columns 3 and 4 controlled for demographic and behavioral characteristics. Estimates from the Logit regressions support the findings previously described. First, the *pure mental representation condition* showed a positive and significant effect, meaning that after the subjects watched the video relating the benefits of eating healthy, their probability of choosing the healthy snack increased. More importantly, when the treatment variables interact with the weight categories they are positive and significant. This means that the *pure mental representation condition* was effective for both overweight and obese individuals. When looking at the *episodic prospection condition*, estimates showed that the probability of choosing the healthy alternative significantly increased only for overweight individuals, and had no effect on obese subjects. As mentioned before, this effect may be due to lack of motivation of obese subjects to attain the goal of becoming healthier as it might require high levels of effort with low immediate results.

Regarding the effects of demographics and behavioral characteristics, estimates from columns 3 and 4 show that the coefficients related to cognitive ability and exercise are positive. The result regarding exercising is not surprising since it was expected that people who exercise on a regular basis are better conditioned to keep a healthy lifestyle and eat healthier foods. In this regard, evidence from previous research has found a positive relationship between exercising and self-control exertion; that is, individuals who exercise regularly have higher self-control ability compared to those who do not exercise regularly (Wang, Rao, and Houser 2015, Palma et al. 2017).

Furthermore, the effect of cognitive function implies that on average, individuals with higher cognitive ability are more likely to choose healthy over unhealthy food products. A study conducted by Ward and Mann (2000) found that high cognitive ability causes restrained eaters (dieters) to over consume food products while the opposite effect is found for unrestrained eaters. The fact that males were less likely to choose the healthy foods can be linked to previous evidence that found a higher probability for men to lack willpower and thus be more prompted to be obese than females (Zhang and Rashad 2008). The results previously described points out the importance of setting achievable and realistic weight loss goals since the impact that treatments has on individuals depends on specific health characteristics such as BMI.

Table 3. Logit regressions on healthy food choices.

Variables	(1)	(2)	(3)	(4)
Pure Mental Representation	0.331 ***	0.119	0.296 ***	0.115
	(0.083)	(0.104)	(0.088)	(0.108)
Episodic Prospection	0.068	-0.100	0.002	-0.131
	(0.082)	(0.101)	(0.087)	(0.105)
Overweight[1]		-0.241	0.225 ***	-0.188
		(0.148)	(0.087)	(0.159)
Obese[2]		-0.208	0.090	-0.138
		(0.175)	(0.105)	(0.191)
Overweight × Pure Mental R.		0.660 ***		0.609 ***
		(0.206)		(0.215)
Overweight × Episodic Prospection		0.634 ***		0.580 ***
		(0.205)		(0.214)
Obese × Pure Mental R.		0.439 *		0.451 *
		(0.243)		(0.255)
Obese × Episodic Prospection		0.227		0.194
		(0.246)		(0.264)
Cogscore			0.031 ***	0.026 ***
			(0.011)	(0.012)
Impatience			0.011	0.013
			(0.008)	(0.008)
Exercise			0.002 *	0.002
			(0.001)	(0.001)
Smoke			0.024	0.041
			(0.153)	(0.154)
Healthiss			0.082	0.138
			(0.242)	(0.257)
Hungry			0.034	0.025
			(0.070)	(0.071)
Male			-0.186 ***	-0.181 ***
			(0.072)	(0.073)
Race2 (Hispanic)			-0.095	-0.082
			(0.101)	(0.102)
Race3 (Other)			0.010	0.017
			(0.085)	(0.088)
Constant	-0.020	0.056	-0.648 ***	-0.473 **
	(0.058)	(0.071)	(0.227)	(0.236)
Log-Likelihood	-2466.896	-2456.572	-2427.516	-2421.561
Observations	3580	3580	3540	3540

Note: Standard deviations are reported in parentheses.

[1] The variable Overweight corresponds to individuals with BMI between 25 and 29.99.

[2] The variable Obese corresponds to individuals with BMI>= 30.

4. Conclusions

Given the tremendous increase in obesity, several policy interventions have been designed in order to promote healthy diets and physical activity. In this paper, we highlight the importance of creating customized programs and interventions targeting specific groups according to their specific health characteristics for setting Achievable and Realistic goals. In doing so, we utilize behavioral economics and biometric tools to analyze whether inducing health-related thoughts and self-image representations influence the behavior of normal weight, overweight, and obese individuals.

We find that the provision of information about the benefits of eating healthy and exercising had a positive impact on overweight and obese individuals. However, when obese individuals are exposed to images of both, their healthier and unhealthier selves, the opposite effect was found. We attribute this effect to the possibility that obese individuals look at the reward of becoming healthier difficult to achieve or somewhat unreachable. The self-consciousness of their appearance may play a role in their motivation (or lack thereof) for having healthy lifestyles.

The results found here can be used to improve the design of policy interventions for weight loss programs. By tailoring programs to the individuals' specific health characteristics, programs can appeal to different priorities and goal setting. Tailoring of feasible targets can keep individuals engaged and translate into higher compliance and better outcomes. For instance, while using education about the benefits of healthy diets and exercising works well for overweight and mildly obese individuals, we found that self-image related or long term rewards work poorly for obese subjects, who might require more tangible or plausible immediate results.

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Appendix A.

Figure A1. Example of products displayed in Food Choice Task.

Appendix B.

Table B1. List of food products used in food choice task.

Unhealthy Snacks	**Healthy Snacks**
Classic Lays potato chips (160 cal.)	Oven-baked Lays potato chips (120 cal.)
Original Fiber One chewy bar (140 cal.)	90 – Calorie Fiber One chewy bar (90 cal.)
Original Jell-O gelatin (70 cal.)	Low calorie Jell-O gelatin (10 cal.)
Original Sargento string cheese (80 cal.)	Reduced fat Sargento string cheese (50 cal.)
Original Pringles potato chips (150 cal.)	Fat free Pringles potato chips (70 cal.)
Original Yoplait yogurt (150 cal.)	Light Yoplait yogurt (90 cal.)
Original Snack Pack pudding (110 cal.)	Sugar free Snack Pack pudding (70 cal.)
Traditional Oikos Greek yogurt (150 cal.)	Non-fat Oikos Greek yogurt (120 cal.)
Original Cheez-It baked crackers (150 cal.)	Reduced fat Cheez-It baked crackers (130 cal.)
Original Jif peanut butter (250 cal.)	Reduced fat Jif peanut butter (250 cal.)
Original Gatorade beverage (80 cal.)	Low calorie Gatorade beverage (30 cal.)
Original Quaker chewy bar (140 cal.)	Low fat Quaker chewy bar (90 cal.)
Original Ritz crackers (80 cal.)	Whole wheat Ritz crackers (70 cal.)
Traditional Lipton green tea (100 cal.)	Diet Lipton green tea (0 cal.)
Original Great Value ice cream sandwich (160 cal.)	97% fat free Great Value ice cream sandwich (110 cal.)
Xtreme butter ACI II popcorn (160 cal.)	94% fat free ACI II popcorn (130 cal.)
Original BelVita biscuits (230 cal.)	Soft baked BelVita biscuits (190 cal.)
Original Jell-O swirls pudding (110 cal.)	Reduced calorie Jell-O swirls pudding (60 cal.)
Original Dole peaches (70 cal.)	No sugar added Dole peaches (25 cal.)
Classic coca cola can (90 cal.)	Zero calorie coca cola can (0 cal.)

Appendix C.

Table C1. Time Preference Survey

Payoff Alternative	Payment Option A (Pays **today**)	Payment Option B (Pays in **2 weeks**)	Preferred Payment Write A or B
1	$10.00	$10.50	
2	$10.00	$11.00	
3	$10.00	$11.50	
4	$10.00	$12.00	
5	$10.00	$12.50	
6	$10.00	$13.00	
7	$10.00	$13.50	
8	$10.00	$14.00	
9	$10.00	$14.50	
10	$10.00	$15.00	
11	$10.00	$15.50	
12	$10.00	$16.00	
13	$10.00	$16.50	
14	$10.00	$17.00	
15	$10.00	$17.50	