Research Article

Psychological Science
2015, Vol. 26(2) 122–134

Reprints and permissions:
sagepub.com/journalsPermissions.nav
DOI: 10.1177/0956797614559543
pss.sagepub.com

Dietary Self-Control Is Related to the Speed With Which Attributes of Healthfulness and Tastiness Are Processed

Nicolette Sullivan[1,2], Cendri Hutcherson[1], Alison Harris[3], and Antonio Rangel[1,2]
[1]Division of Humanities and Social Sciences, California Institute of Technology; [2]Computation and Neural Systems, California Institute of Technology; and [3]Department of Psychology, Claremont McKenna College

Abstract
We propose that self-control failures, and variation across individuals in self-control abilities, are partly due to differences in the speed with which the decision-making circuitry processes basic attributes, such as tastiness, versus more abstract attributes, such as healthfulness. We tested these hypotheses by combining a dietary-choice task with a novel form of mouse tracking that allowed us to pinpoint when different attributes were being integrated into the choice process with temporal resolution at the millisecond level. We found that, on average, tastiness was processed about 195 ms earlier than healthfulness during the choice process. We also found that 13% to 39% of observed individual differences in self-control ability could be explained by differences in the relative speed with which tastiness and healthfulness were processed.

Keywords
decision making, self-control, food, delay of gratification, individual differences, open data, open materials

Received 11/19/13; Revision accepted 9/27/14

A large fraction of the population struggles with dietary self-control. For these people, a choice between an apple and a chocolate chip cookie is more difficult than a choice between an apple and an orange, and is also more likely to result in decision mistakes (Rangel, 2013). This leads to two basic questions: Why is sustained dietary self-control so difficult for so many? Why do some individuals have better self-control than others?

These important questions have received considerable attention in several disciplines, including economics, psychology, and neuroscience. Behavioral economists conceptualize self-control failures as instances in which individuals overdiscount the future consequences of their decisions (Ikeda, Kang, & Ohtake, 2010; Laibson, 1997; O'Donoghue & Rabin, 1999). Related to this idea is the proposal that dietary self-control is hard because of inherent limitations in how people process two different types of attributes (Liberman & Trope, 2008). In this view, basic attributes, such as the anticipated tastiness of foods, are easily represented at the time of choice and reliably weighted in decisions. In contrast, taking into account more abstract attributes, such as the healthfulness of foods, is thought to require effort, and as a result, these attributes are not weighted as reliably in decisions. This leads to a relative overweighting of taste compared with health information, which can result in poor dietary choices. Neuroscientists have identified neural mechanisms underlying the differences between how tastiness and healthfulness are computed at the time of decision in people with good and poor self-control (Hare, Camerer, & Rangel, 2009). In both groups, areas of ventromedial

Corresponding Author:
Nicolette Sullivan, California Institute of Technology, Humanities and Social Sciences, 121 Baxter Hall, Pasadena, CA 91125
E-mail: nsulliva@caltech.edu

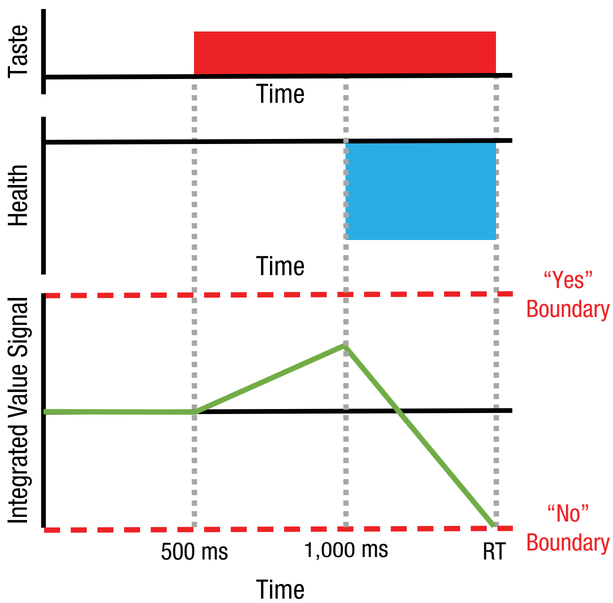

Fig. 1. Illustration of how the time at which attributes are computed could affect choices in sequential integrator models of choice. Consider an example in which the subject needs to decide whether to eat a food that is a little tasty but very unhealthy. Suppose also that taste information is computed from 500 ms until a decision is made, whereas health information is computed only after 1,000 ms. A choice is made by computing a dynamic value signal that starts at zero and sequentially integrates a weighted linear sum of the attributes represented at this time plus noise. These weights can be interpreted as the true preferences that the individual is trying to maximize. A choice is made the first time the integrated value signal crosses one of the two preestablished barriers: "yes" to eat the item and "no" to decline it. For simplicity, the integrated value signal is depicted without noise. The gap in processing times then implies that only taste information affects the value signal between 500 and 1,000 ms, which increases the likelihood that an unhealthful choice will be made. RT = reaction time.

prefrontal cortex (vmPFC) represent the overall value assigned to the food. However, in individuals with poor self-control, this area responds only to the taste of foods, whereas in individuals with good self-control, it responds to both health and taste information. Furthermore, in individuals with good self-control, areas of left dorsolateral prefrontal cortex seem to modulate value-related activity in vmPFC.

We propose that dietary self-control failures are partly due to differences in the speed with which the decision-making circuitry processes basic attributes, such as tastiness, versus more abstract attributes, such as healthfulness. To investigate this idea, we tested two explanations for the questions posed in the first paragraph. First, we hypothesized that dietary self-control is difficult for many because, on average, tastiness attributes are processed earlier than healthfulness attributes. Second, we hypothesized that individual differences in dietary self-control abilities are related to differences in the relative speed with which tastiness and healthfulness attributes are processed. In particular, does the ability to deploy self-control decrease with increasing delays of the start of health-information processing, relative to taste-information processing?

These two hypotheses were inspired by a robust implication of several models of choice, including decision-field theory (Busemeyer & Townsend, 1993); the drift-diffusion model (Ratcliff & McKoon, 2008); and the leaky, competing-accumulator model (Usher & McClelland, 2001). As illustrated in Figure 1, these models assume that the brain makes decisions by computing a dynamic signal that measures the value of two possible responses: for example, choosing to eat a cookie ("yes") or declining it ("no"). At every instant, the signal estimates the relative value of "yes" by adding a noisy measure of the value of the item, given by a weighted linear combination of the item's attributes plus some Gaussian noise. A choice is made the first time one of two preestablished barriers is crossed: "yes" if the upper one is reached first and "no" if the lower one is reached first. A critical feature of this model is that an attribute can affect the evolution of the value signal only if it is being represented at that instant. Thus, as in Figure 1, if taste information is processed starting at 500 ms, but health information is processed only starting at 1,000 ms, then during the interim, the value signal is influenced only by taste information. This would move the signal closer to the choice to eat the cookie and decrease the likelihood of declining it. In fact, if the onset of health-information processing is sufficiently delayed, a choice will be made before it can influence the decision at all.

These hypotheses are related to the previous literature (Hare et al., 2009), but we posit a different and novel mechanism underlying difficulties in the ability to exercise self-control. The emphasis in the present study was on the *speed* at which attributes are processed and not on differences in the ability to process the attributes or on how they would be weighted under the individual's true preference (i.e., if choices could be made without noise). In particular, differences in the speed of processing can generate differences in the relative influence of healthfulness and tastiness on the final decision, but such weighting differences need not be due to differences in processing speed. This distinction is important because many contextual variables (e.g., time pressure) could have a direct effect on the relative speed at which different attributes are computed without directly affecting how they influence choice.

To test these hypotheses, it is necessary to have a dynamic measure of the extent to which different attributes are integrated into the choice process while the decision is being made and for this measure to provide subsecond temporal resolution. Building on the pioneering mouse-tracking literature (Dale, Kehoe, & Spivey, 2007; Dshemuchadse, Scherbaum, & Goschke, 2013; Freeman & Ambady, 2009; Freeman, Ambady, Rule, & Johnson, 2008; McKinstry, Dale, & Spivey, 2008; Song & Nakayama, 2008; Spivey, Grosjean, & Knoblich, 2005), we asked subjects to indicate their choice between two options using a continuous computer-mouse movement. By measuring the mouse positions along the trajectory, we can infer the state of the choice process prior to the final decision. Scherbaum, Dshemuchadse, and Goschke (2012) propose a related link between connectionist models and intertemporal choice.

Method

Subjects

Twenty-eight students (25% female, 75% male; 93% right-handed) participated in the experiment, which was approved by the California Institute of Technology's Institutional Review Board. Subjects received \$25 for their participation. They were asked to fast for 4 hr prior to the experiment. Compliance with this instruction was monitored by self-report.

Task

Subjects performed three tasks, always in the same order. First, over three separate blocks, they rated 160 different foods in terms of (a) tastiness ("How tasty is this food?"), (b) healthfulness ("How healthy is this food?"), and (c) overall liking ("How much would you like to eat this food at the end of the experiment?"). Block and stimulus order were randomized across subjects. All ratings were made on a 5-point scale (−2, *very little*, to 2, *very much*). On the basis of pretesting, we selected food stimuli in which healthfulness and tastiness had minimal correlation for a typical subject (r = .2, p < .001). The foods included fruits, candies, chips, and granola bars. On every rating trial, a single color image was presented at the center of the screen (~5.6 × 4.3 in.), on a black background, and in high resolution (1,680 × 1,050 pixels) on 20.1-in., 96 dots-per-in. LCD monitors.

Second, subjects were asked to read a short excerpt from WebMD.com on the importance of healthy eating (see Fig. S1 in the Supplemental Material available online). This was done to increase the frequency with which they exhibited dietary self-control in the subsequent food-choice task.

Third, subjects made 280 binary choices among randomly selected pairs of foods. Food pairs were selected so that all possible combinations of tastiness and healthfulness ratings were equally represented (excluding any foods rated as neutral in either category). Choices were made in 40-trial blocks, with short rests in between. There were two types of trials. In six randomly selected blocks, subjects used the mouse to indicate their choice (mouse trials). In the other block, they used the keyboard to enter their response (keyboard trials). Subjects were informed of the type of the trial at the beginning of each block.

Figure 2a depicts a typical mouse trial. The trial began with the display of a box containing the word "START" at the bottom center of a black screen. Subjects had to click in this box to start the trial. This was followed by a blank screen of random duration drawn from a uniform distribution of 200 to 500 ms (mean duration = 350 ms), during which the mouse cursor disappeared from the screen. At the end of this blank screen, the mouse cursor reappeared in the bottom center of the screen, where the start box used to be, and pictures of two foods appeared, one at the top left and one at the top right of the screen, respectively, each surrounded by a white box (174 × 131 pixels).

Subjects were instructed to select which of the two foods they preferred by moving the cursor continuously to the box inside which their preferred food was displayed. The location of foods (left vs. right) was completely randomized. Once the subject clicked inside one of the food boxes, a choice was recorded. Subjects could take as long as they wanted to make their response, but they were instructed to respond as quickly and accurately as possible. The foods did not appear until a mouse movement was detected. This was done to promote fluid mouse movements during the choice process. Cursor velocity was significantly greater than zero for normalized Time Points 1 through 99 (two-tailed t test; p < .01, uncorrected for multiple comparisons; see the Time Normalization section below), which suggests that movements were fluid on average. Trials were separated by a fixation of random duration (400–700 ms; M = 550 ms).

Keyboard trials had a structure identical to that of mouse trials, except for the following differences. Subjects kept two fingers over the keyboard buttons associated with left and right responses at all times and did not use the mouse. Trials were initiated by pressing the space bar. Foods appeared automatically after the blank screen preceding the food display. Subjects indicated their choices by pressing the left or right keys.

Subjects were incentivized to care about their choices by giving them, at the end of the experiment, one food they chose on a single, randomly selected trial. Subjects were asked to remain in the lab following the choice task until they had eaten the food or 30 min had expired, whichever occurred first. Since they did not know in advance which trial would be selected, their best strategy was to treat every choice as if it were the only one.

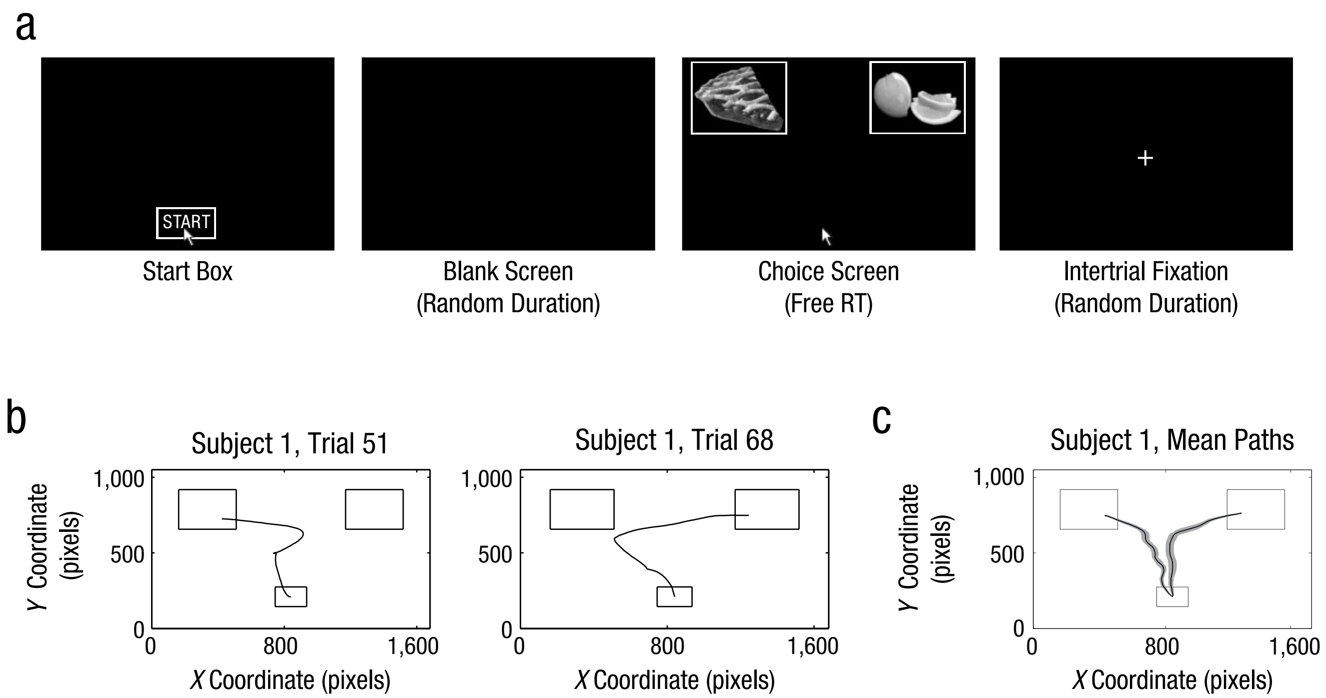

Fig. 2. The mouse-tracking choice task. Each trial (a) began when participants clicked the start box. After a blank screen, participants were shown two pictures, each of which depicted a different food, and they had to move the cursor continuously, starting from its position at the bottom of the screen, to select one. Two representative mouse paths for Subject 1 are shown in (b) for trials on which the left-hand food and the right-hand food, respectively, were selected. Mean paths for the same subject are shown in (c). RT = reaction time.

Mouse tracking

During mouse trials, the cursor's *x,y* position was tracked using the Psychophysics Toolbox (Brainard, 1997) with a temporal resolution of 67 Hz. For our analyses, we shifted and normalized the coordinates so that the center of the start box—the location at which the cursor appeared—was at (0,0), the pixel clicked to select the left option was at (−1,1), and the pixel clicked to select the right option was at (1,1).

Data preprocessing

To reduce some of the noise caused by trials on which subjects seemed to have difficulty complying with the instruction to make continuous and rapid mouse movements, we applied two preprocessing steps to the mouse data. First, for each subject, mouse trials with reaction times (RTs) greater than two standard deviations above their mouse-trial mean were excluded from further analysis (13.3% of all trials). The mean RT in mouse trials was 1,814 ms (SD = 524 ms). Second, we also removed a small fraction of trials in which the mouse trajectory crossed the *y*-axis more than three times (a mean of 3.3% of trials per subject; 26 of 28 subjects had at least one such trial). In contrast, as illustrated in Figure 2b, most trials involved one or two changes of direction. These criteria were selected a priori, were not based on their effect on the analyses, and did not have a qualitative impact on the results.

Time normalization

To facilitate comparison across trials with large differences in RTs, we normalized time in most of the analyses. In particular, the duration of every trial was sliced into 101 time bins of identical length, with the start position at (0,0) designated as t = 1 and the time a choice was recorded as t = 101. Thus, the index t provides a measure of normalized time.

We also carried out all of the analyses using absolute time and found similar but noisier qualitative results. We believe that this is due to sizable cross-subject differences in RTs, which might reflect differences in underlying cognitive-processing speeds. Such differences would render these analyses problematic, because absolute time would then reflect different stages of cognitive processing in different subjects. In contrast, this issue does not arise in the time-normalized analyses.

Trajectory analyses

We conducted two types of trajectory analyses. First, we estimated several linear regressions of how the trajectory angle at every normalized time point was affected by the attributes of the foods. The trajectory angle at time t provided a measure of the angle between t and $t + 1$ and was normalized such that −45° always indicated a direct movement toward the left item, 0° always indicated a movement straight upward, and +45° always indicated a direct movement toward the right item. These regressions were estimated at the individual level, and then the relevant estimated coefficients were pooled across subjects.

We also used the results from these regressions to identify the earliest (normalized) time at which various properties of the foods had a significant and lasting influence on the trajectories. This was done by carrying out a one-tailed test of the hypothesis that the estimated regression coefficient of interest would be significant at the 5% level, for each individual and time index. We used one-tailed tests because we were interested in when they would become positively significant. The earliest time window at which the test was satisfied was then labeled as the earliest time at which the variable of interest had a significant positive impact on the mouse trajectory for that subject. Notably, the test requires that the variable maintain its significance from that time point through the end of the trial. Group comparisons were then performed using two-sided t tests on the relevant distribution of individual statistics. For expositional reasons, further details on the trajectory analyses are provided in the relevant parts of the Results section.

Results

To test whether the relative speed with which tastiness and healthfulness are computed affects dietary self-control, it was necessary to have a good measure of how the influence of these attributes evolves over the decision process. Here, we constructed such a measure by asking subjects to indicate their choice using a continuous mouse movement, with positions along the trajectory serving to measure the state of the choice process prior to the final decision. This was a critical aspect of our experiment because it allowed us to identify, prior to the final decision, the time at which the tastiness and healthfulness attributes began influencing choice. The method was justified as long as movements of the computer mouse were correlated, at every instant, with changes in the integrated value signal illustrated in Figure 1. In this case, if the trajectory of the mouse at time t was affected by health information, then we could conclude that the underlying relative value signal of interest was also being modulated by healthfulness at that time.

To see the power of this technique, consider a hypothetical example. Suppose that the mouse trajectories for a given subject have the following two properties. First, the relative position between the left and right options, as measured by x-position, is significantly related to the relative tastiness rating of the items on the left and right (i.e., $\text{tastiness}_{\text{right}} - \text{tastiness}_{\text{left}}$) after 300 ms but not before. Second, the x-position is also related to the relative healthfulness rating of the foods on the right and the left (i.e., $\text{healthfulness}_{\text{right}} - \text{healthfulness}_{\text{left}}$) after 800 ms but not before. Then we could conclude that attributes of tastiness were processed by the choice circuitry 500 ms earlier than attributes of healthfulness. Furthermore, the technique allowed us to test whether differences in the earliest time at which health and taste information were processed could explain differences in dietary self-control across individuals.

Paradigm validation

We began the analysis by carrying out several tests designed to address concerns about the validity of the paradigm. One natural concern is that requiring subjects to indicate their choices with a mouse, instead of more common methods, such as a button press, might affect the choices or the computations of the choice circuitry. To address this concern, we asked subjects to make otherwise identical choices using either the keyboard or the mouse, and then we compared the behavior in both conditions. Figure 3a depicts the average choice curve for each condition, plotting the probability of choosing left against the relative value of the left item (measured by $\text{liking}_{\text{left}} - \text{liking}_{\text{right}}$).

We found that the two methods of choosing led to indistinguishable choice curves (mouse: mean logistic slope = −0.37; keyboard: mean logistic slope = −0.33), $t(27) = 1.25$, $p = .22$ (two-tailed). Figure 3b plots mean RT as a function of choice difficulty (measured by $|\text{liking}_{\text{left}} - \text{liking}_{\text{right}}|$). RTs were longer in the mouse condition (M = 1,814 ms) than in the keyboard condition (M = 1,258 ms), $t(27) = 4.54$, $p = .0001$ (two-tailed), likely because of the additional motor complexity of the mouse-tracking task. However, in both cases, RTs decreased with choice difficulty (mouse: mean linear regression slope = −0.036; keyboard: mean linear regression slope = −0.051), $t(27) = -1.36$, $p = .18$ (two-tailed). This pattern is a common property of binary choice (Ashby, 1983; Luce, 1986; Milosavljevic, Malmaud, Huth, Koch, & Rangel, 2010; Ratcliff & Rouder, 1998; Rolls, Grabenhorst, & Deco, 2010) and a key prediction of the type of integrator models of decision making discussed in the introduction. These results suggest that the nature of the choice process was not substantially altered by the use of mouse tracking.

Another natural concern is that the mouse trajectories might not provide a good measure of the extent to which the properties of the foods are dynamically incorporated in the decision process. This could happen, for example, if individuals always made their decision before moving

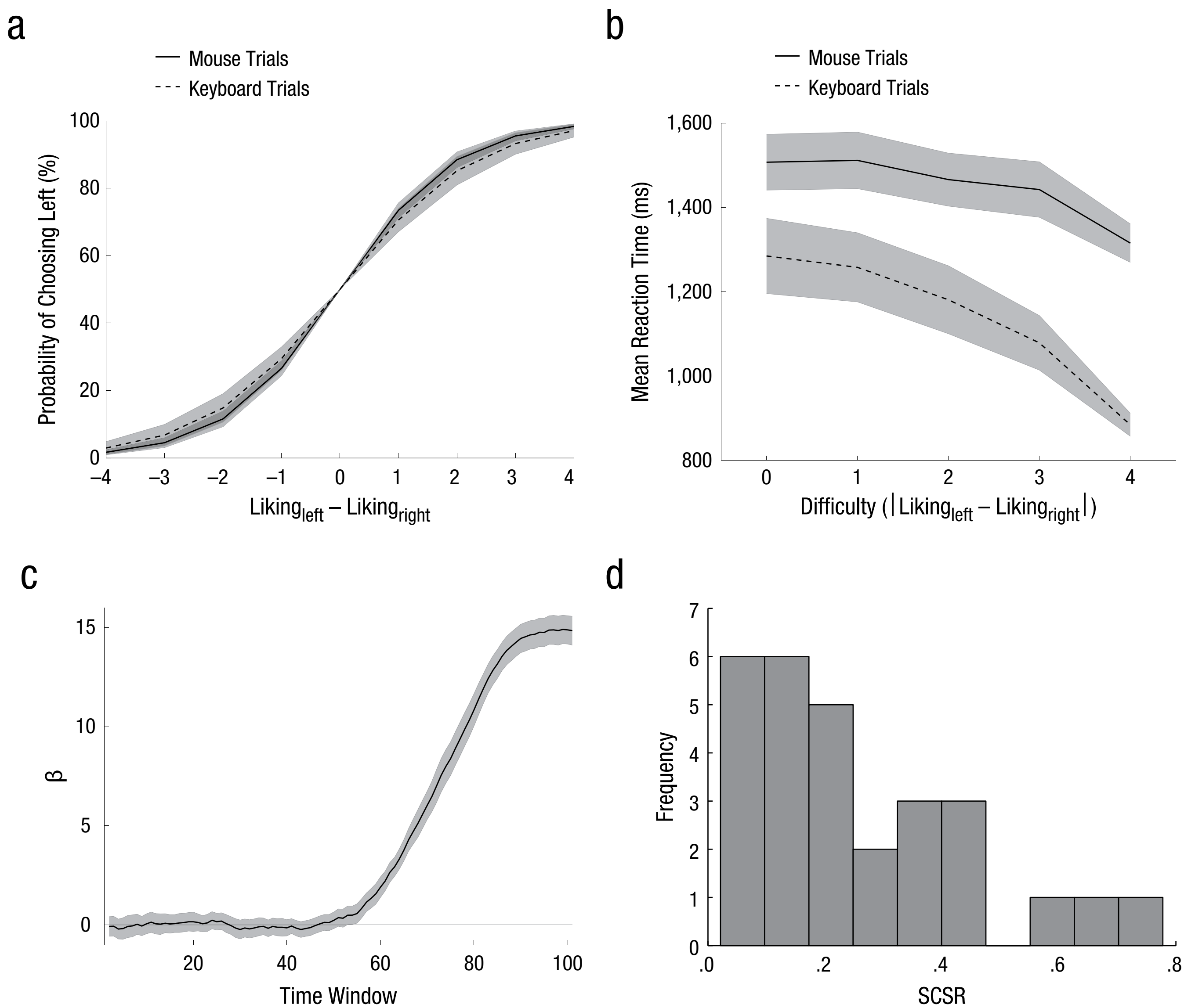

Fig. 3. Results of the analyses validating the paradigm. Average psychometric choice curves for mouse and keyboard trials (a) are plotted for the probability of choosing left as a function of the relative value of the left item over the right item. Mean reaction time in mouse and keyboard trials (b) is shown as a function of choice difficulty, as measured by the absolute value of the difference between liking for the right item and for the left item. A 0 indicates a difficult choice between two equally liked foods, and a 4 indicates an easy choice between foods with opposite liking ratings. The graph in (c) depicts the results of a regression analysis showing the impact of the relative value of the right item over the left item ($\text{liking}_{\text{right}} - \text{liking}_{\text{left}}$) on the mouse's angle trajectory, measured at each normalized time window. Error bands in graphs (a–c) denote standard errors computed across subjects. The distribution of self-control-success ratios (SCSRs) across subjects is shown in (d). The SCSR was defined as the fraction of trials in which self-control was successfully exercised when subjects were presented with one food that had a higher healthfulness rating and another food that had a higher tastiness rating.

the mouse and then made a very rapid straight movement to the chosen option. The paths depicted in Figures 2b and 2c suggest that this was not the case, but we also conducted a more rigorous test. For each normalized time window and each individual, the local angle trajectory was regressed against the relative value of the two options (as measured by $\text{liking}_{\text{right}} - \text{liking}_{\text{left}}$). The estimated slope, plotted in Figure 3c across the 101 time windows, provides a measure of the extent to which the value information influenced the choice process at different times. We found that, across subjects, the earliest time point at which the value information had a sustained, significant effect on the trajectories, without ever returning to being nonsignificant, was 56. Furthermore, the impact of value rose gradually over the course of the trial. In contrast, if subjects had made their choice before moving their mouse and then had responded very rapidly with a straight trajectory, the time course depicted in

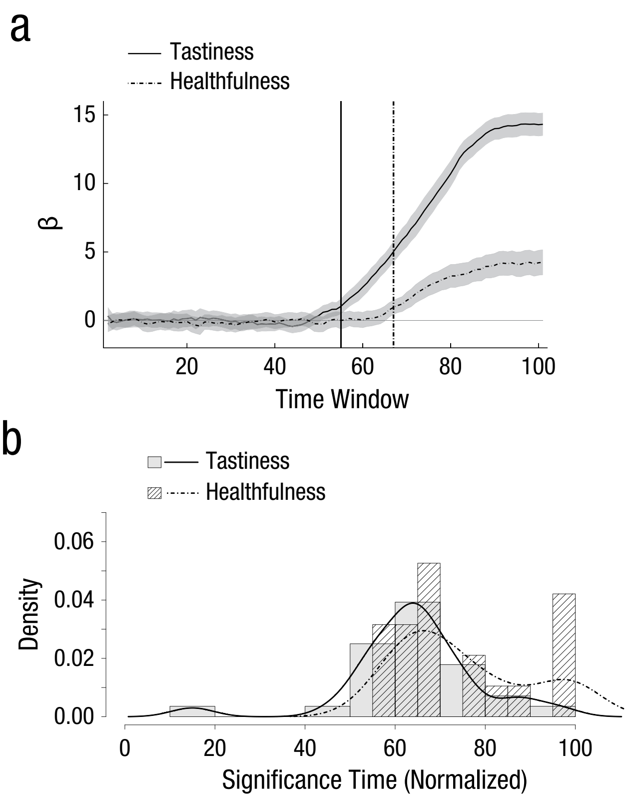

Fig. 4. Effect of taste and health attributes on mouse trajectories. Results from the regression analyses exploring the mean effect of the relative tastiness of the right item over the left item (tastiness_{right} – tastiness_{left}) and the relative healthfulness of the right item over the left item ($\text{healthfulness}_{right}$ – $\text{healthfulness}_{left}$) is shown in (a) for each normalized time window. Error bands denote standard errors. Vertical lines indicate the earliest time at which the effect of each attribute became significantly greater than zero without subsequently becoming nonsignificant. The distribution of individual estimates of the earliest time at which each attribute significantly affected the trajectory is shown in (b).

Figure 3c would look approximately like a step function. The resulting coefficients suggest that the information about the choice options was incorporated gradually into the choice process and that the magnitude of the effect could be measured with our methodology.

Finally, we tested whether there was cross-subject variation in the ability to exercise dietary self-control. This is important because we were interested in the extent to which individual differences in self-control could be explained by differences in the speed with which tastiness and healthfulness attributes are computed. To measure self-control success for each subject, we first divided trials into those that entailed a self-control challenge and those that did not. Challenge trials involved a choice between two foods, in which one food had a higher healthfulness rating and the other had a higher tastiness rating. In this case, successful self-control occurred when the subject chose the healthier item, whereas choosing the tastier item constituted a self-control failure. In contrast, in nonchallenge trials, one of the items had a higher rating in both dimensions, and thus there was no need to exercise self-control. Given this, we defined a subject's self-control-success ratio (SCSR) to be the fraction of challenge trials in which self-control was successfully exercised. Figure 3d, which depicts the distribution of SCSRs across subjects, shows that there was substantial variation across subjects (M = 25%, range = 2–78%). There were no significant RT differences between challenge trials (M = 1,782 ms) and nonchallenge trials (M = 1,701 ms), $t(27) = 0.78$, $p = .44$ (two-tailed), which is consistent with the hypothesis that subjects utilized a similar decision process in both types of trials.

Tastiness and healthfulness in the choice process

To test whether taste information influenced the choice process earlier than health information, we examined how mouse-angle trajectories across successive normalized time windows were weighted on taste and health information. For every subject and time window, we estimated a linear regression of the angle trajectory on relative tastiness (tastiness_{right} – tastiness_{left}) and relative healthfulness ($\text{healthfulness}_{right}$ – $\text{healthfulness}_{left}$). The resulting estimated coefficients provide a measure of the extent to which each attribute influences the choice process at that time window. Figure 4a summarizes the effect of these regressions by plotting the mean time course of the estimated coefficients, as well as the times at which the distribution of estimates for the group first became significantly larger than zero without ever returning to being nonsignificant. As hypothesized, mouse trajectories were influenced by tastiness at significantly earlier time windows (t = 55) compared with healthfulness (t = 67; $p < .05$ threshold, one-tailed).

We carried out an additional test of the same hypothesis by estimating the earliest normalized time at which the effect of each attribute became significant without subsequently becoming nonsignificant, separately for each individual, and then comparing their distributions. We found that healthfulness never became a significant influence on the trajectory for 32% of subjects, whereas for tastiness this happened for no subjects. Furthermore, as shown in Figure 4b, we also found that the mean earliest time for a significant effect of healthfulness was later than the mean earliest time for tastiness (mean difference = 9.11), $t(18) = -1.97$, $p = .032$ (one-tailed).

Together, these results suggest that, on average, taste information began to influence the choice process about 9% earlier than health information. Given the average duration of the trials, this corresponded to an onset of

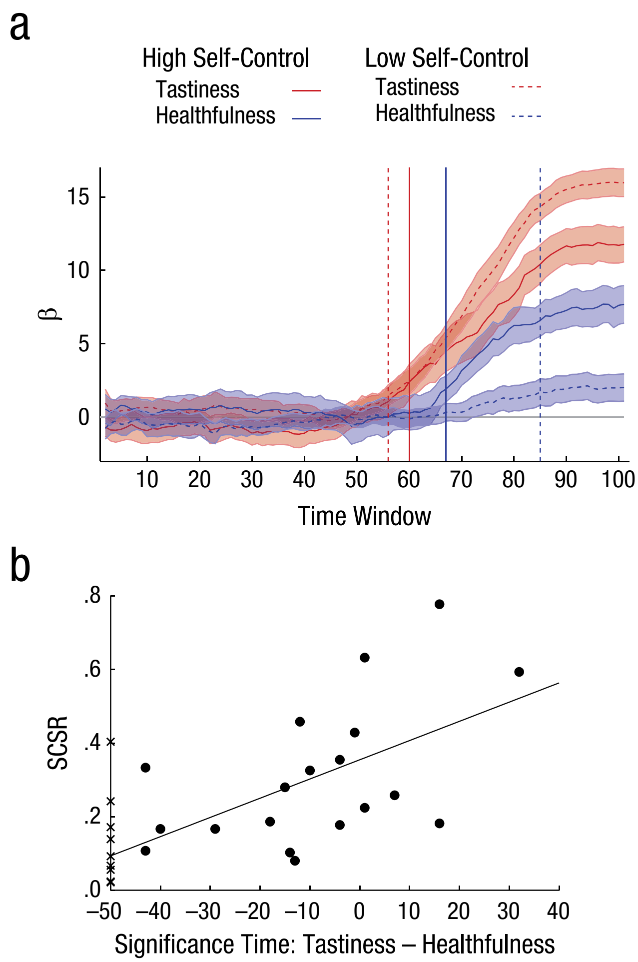

Fig. 5. Individual differences in self-control. The graph (a) shows results from the regression analyses exploring the effect of the relative tastiness of the right item over the left item ($\text{tastiness}_{\text{right}} - \text{tastiness}_{\text{left}}$) and the relative healthfulness of the right item over the left item ($\text{healthfulness}_{\text{right}} - \text{healthfulness}_{\text{left}}$) on the mouse trajectory for each time window, computed separately for individuals with high and low self-control (defined using a median split). Error bands denote standard errors. Vertical lines indicate the earliest time at which each attribute became significantly different from zero. The scatter plot in (b; with best-fitting regression line) shows each subject's self-control-success ratio (SCSR) as a function of the difference between the earliest time at which healthfulness became significant minus the earliest time at which tastiness became significant. Circles indicate subjects for whom both tastiness and healthfulness had a significant effect on trajectories before the end of the trial. Crosses indicate subjects for whom these attributes did not have a significant effect on trajectories; for those subjects, the value of the earliest time for health was set to 102.

health-attribute processing by the choice circuitry approximately 195 ms later than the onset for tastiness.

Dietary self-control and the speed at which tastiness and healthfulness are computed

To address whether individual differences in dietary self-control were associated with differences in the relative speed at which the healthfulness and tastiness attributes were computed, we began by comparing how taste and health information were reflected in the mouse trajectories for individuals with high versus low self-control, as defined using a median split of the SCSR statistic. As shown in Figure 5a, we found substantial differences across the groups. In particular, in the high-self-control group, the paths for tastiness and healthfulness were quite similar and became significantly greater than zero at approximately the same time (healthfulness: t = 67; tastiness: t = 60). In contrast, for the low-self-control group, the latency at which tastiness became significant was similar to that of the high-self-control group (t = 56), but the latency for healthfulness occurred much later (t = 85). As before, we tested for the significance of these differences by estimating at the individual level the earliest time at which healthfulness became significantly greater than zero and then comparing the distributions. The normalized time at which tastiness and healthfulness became significant did not differ significantly for high-self-control subjects (mean healthfulness: t = 69.50; mean tastiness: t = 68.54; mean difference = −2.9), $t(9) = -0.46$, $p = .33$ (one-tailed), but they were significantly different in the low-self-control group (mean healthfulness: t = 81.22; mean tastiness: t = 61.35; mean difference = −16), $t(8) = -2.5$, $p = .02$ (one-tailed).

Figure 5b takes this analysis a step further. For each subject, we computed a measure of the *computational advantage* of tastiness, given by the earliest time at which tastiness significantly affected and continued to affect the trajectories minus the earliest time at which healthfulness did. We then estimated a linear regression of the SCSR measures of self-control against the individual measures of the computational advantage for tastiness versus healthfulness. This regression tested the extent to which individual differences in self-control could be attributed to individual differences in the relative speed at which the healthfulness and tastiness attributes are processed. Since healthfulness never became significant for 32% of the subjects, we carried out the test in two different ways. In one case, we assumed that for the problem subjects, healthfulness first became significant at t = 102, one time point after the final time point, and estimated the regression using all of the subjects (linear regression slope = 0.005, $p < .0004$, $R^2 = .39$). In the other case, we simply excluded these subjects, carrying out the regression using only the 67.9% of subjects for whom healthfulness became significant during the trial. This yielded a similar result (linear regression slope = 0.005, $p = .02$, $R^2 = .29$).

We also carried out an additional analysis to rule out a potential confound in these results. To understand the concern, suppose that healthfulness and tastiness begin to influence the true data-generation process at the same instant but that, on average, the weight given to

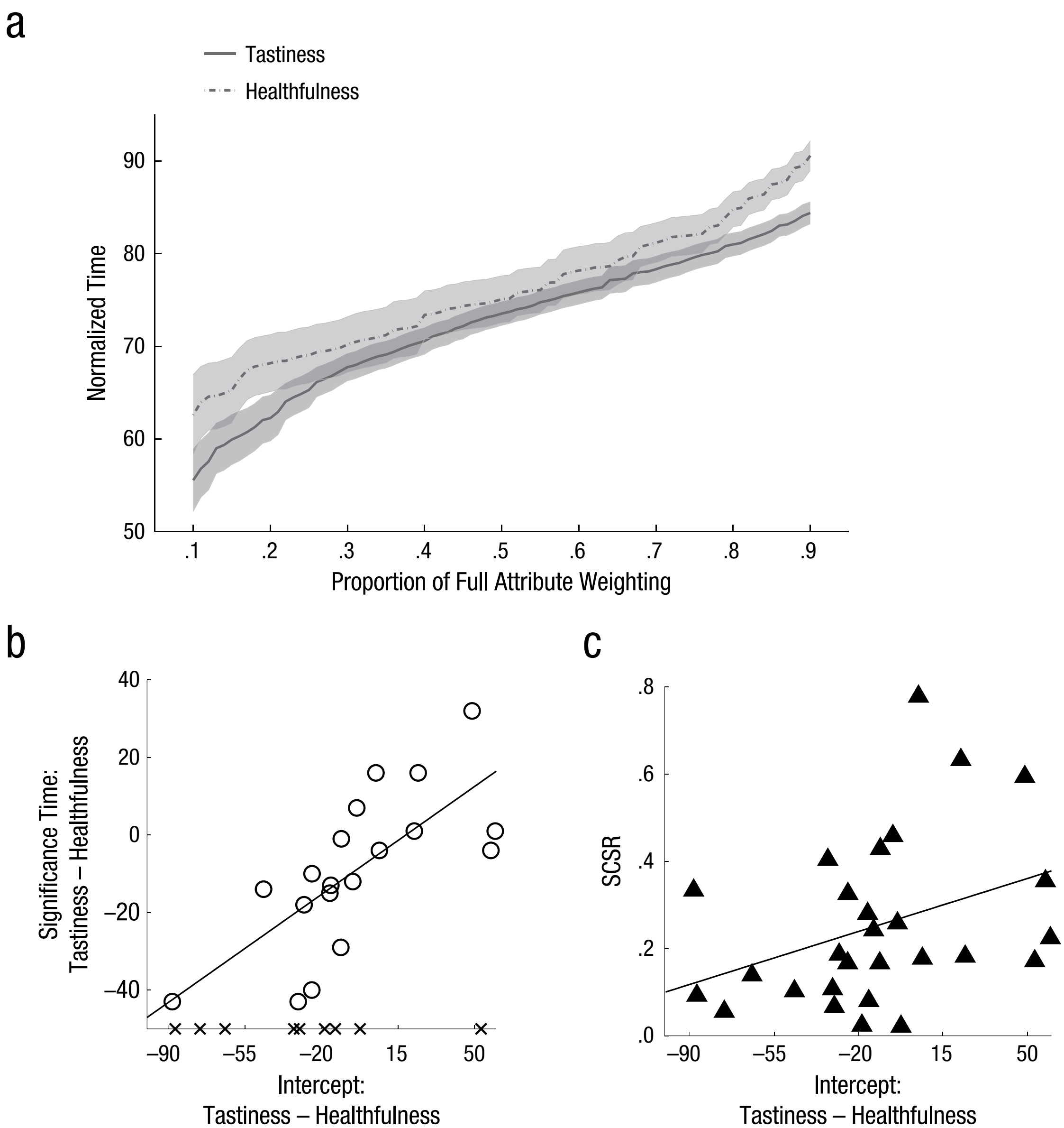

Fig. 6. Results from the control analysis. The graph (a) shows the estimated normalized time at which the weighting of tastiness and healthfulness on cursor trajectory had accumulated a proportion of its final value. Error bands denote standard errors. The cross-subject scatter plot in (b; with best-fitting regression line) shows the relationship between significance time (the earliest time at which tastiness significantly affected the trajectory minus the earliest time at which healthfulness did) as a function of the intercept-based measure of the time advantage of tastiness over healthfulness. Circles indicate subjects for whom healthfulness had a significant effect on trajectories before the end of the trial, and crosses indicate subjects for whom healthfulness did not have such an effect. The cross-subject scatter plot in (c; with best-fitting regression line) shows the correlation between each subject's self-control-success ratio (SCSR) and the intercept-based measure of the time advantage for tastiness.

tastiness in the instantaneous value signal being integrated is larger than the average weight given to healthfulness. In this case, if the noise associated with both signals is sufficiently similar, a test based on significance time will identify an earlier entrance for tastiness than healthfulness purely on the basis of the ratio of the weight to the noise and may falsely overestimate the difference in significant times. Furthermore, this potential bias would be correlated with the relative "true" weights of healthfulness and tastiness, and thus with the SCSR measure, which could lead to a spurious correlation. Figure 6 depicts the results of an analysis designed to control for this problem. For every subject and for every percentile value p between 10% and 90%, we

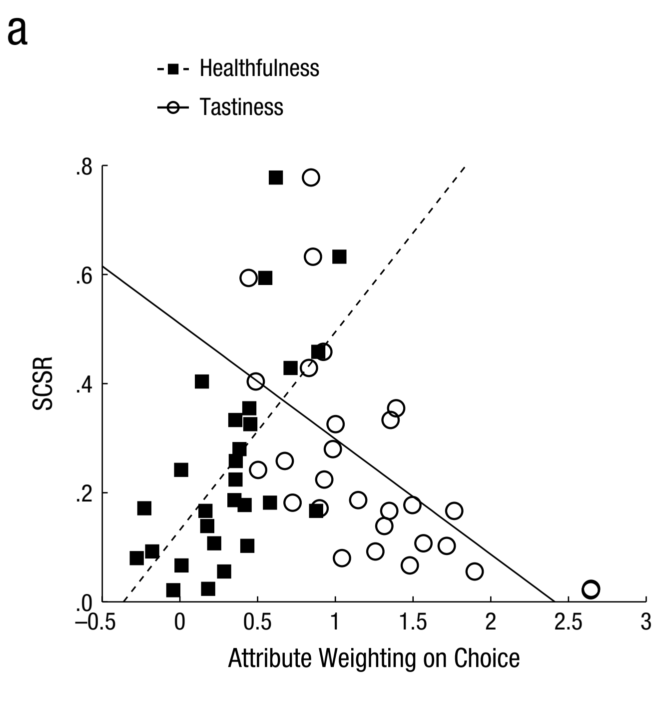

Fig. 7. Relationship between final decision weights and speed of computation. The scatter plot in (a) depicts each subject's self-control-success ratio (SCSR) as a function of final decision weight for the healthfulness and tastiness attributes. Lines denote the best linear fits for the regressions of SCSRs on each of the attribute weights, separately. The scatter plot in (b; with best-fitting regression line) shows relative final decision weight as a function of the earliest time at which tastiness significantly affected the trajectory minus the earliest time at which healthfulness did. Circles indicate subjects for whom healthfulness had a significant effect on trajectories before the end of the trial, and crosses indicate subjects for whom healthfulness did not have such an effect.

used the previous regression results to identify the time at which each of the attributes reaches and never drops below *p*% of its final magnitude. This leads to the plot in Figure 6a, which depicts the speed at which healthfulness and tastiness reach different thresholds. We then fit a cubic polynomial to the estimates of each subject, separately for healthfulness and tastiness, and interpolated its value to the *y*-axis, which provides a measure of the earliest time at which each of the attributes begins and continues to influence the mouse trajectories. Note that this measure does not depend on the final weights that the attributes have on choice and is fairly robust to noise. As shown in Figure 6b, we found that the differences in earliest significant time identified with the previous analysis were highly correlated with those identified with this new method (R^2 = .51, p = .006). Likewise, the alternative measure of the relative earliest times can still significantly predict a sizable fraction of the individual differences in self-control (Fig. 6c; R^2 = .13, p = .059).

Together, these results suggest that a sizable fraction of individual differences in dietary self-control, on the order of 13% to 39%, might be attributable to differences in the relative speed at which the healthfulness and tastiness attributes are processed by the choice circuitry.

Relative computation time and attribute decision weights

The previous results suggest that the relative speed at which healthfulness and tastiness are computed is related to the ability to exercise dietary self-control. We concluded our investigation by carrying out a post hoc analysis to examine further the nature of the relationship. This was done in two steps.

First, Figure 7a depicts the extent to which differences in SCSRs are related to differences in the weights given to the tastiness and healthfulness attributes in the final decision. The plot was constructed as follows. For every subject, we computed a logistic regression of the probability of choosing the right item against relative tastiness ($\text{tastiness}_{\text{right}} - \text{tastiness}_{\text{left}}$) and relative healthfulness ($\text{healthfulness}_{\text{right}} - \text{healthfulness}_{\text{left}}$). This provided individual estimates of the weights that each attribute received on the final decision. We then plotted the individual estimates against the SCSR, and for each type of attribute, we carried out a linear regression of the SCSR measure against the individual estimates. Both attributes were highly significant and, on their own, explained a sizable fraction of the individual differences in self-control (healthfulness: p = .0004, R^2 = .39; tastiness: p = .0004, R^2 = .38).

Second, we hypothesized that the final decision weights for tastiness and healthfulness were influenced by the speed with which the attributes were computed. This hypothesis was based on the idea that the earlier an attribute starts influencing the choice process, the longer it is integrated and thus the stronger its effect on the final choice. This hypothesis is consistent with the type of integrator decision models described in the introduction. To test this hypothesis, we regressed the individual estimates of the final relative decision weight of healthfulness minus tastiness on the computational advantage of tastiness, as defined in the previous section. As shown in Figure 7b, we found that the two variables had a significant and sizable relation (slope = −0.02, p = .001, R^2 = .487).

Given these results, we then hypothesized that the main mechanism through which the speed of attribute processing influences SCSRs is the modulation of the weight assigned to each attribute in the final choice. To test this hypothesis, we carried out a mediation analysis. Using this method, we found that the when the final weight of tastiness was included in the model, tastiness's time to significance was reduced by 79.14%, which made tastiness's time to significance nonsignificant for predicting SCSR (p = .60). This was also true for the healthfulness coefficient, which when added to the model reduced path strength by 88.26%, making healthfulness's time-to-significance nonsignificant for predicting SCSR (p = .75). See Figure S2 in the Supplemental Material for details.

Together, these results suggest that attributes that are computed earlier have a stronger weight in the final decision, likely because the amount of time during which they are integrated into the decision is relatively increased. In particular, this suggests that initial delays in the computation of an attribute are not made up later on during the choice process, for example, by a heavier weighting closer to the time of decision.

Discussion

In this study, we proposed that dietary self-control failures can be traced back to relative differences in the speed with which the decision-making circuitry processes basic attributes, such as tastiness, versus more abstract attributes, such as healthfulness. We found evidence that, on average, tastiness attributes are processed about 195 ms earlier than healthfulness attributes during the choice process. We also found that individual differences in dietary self-control are related to differences in the relative speed with which tastiness and healthfulness are processed. In particular, we found that self-control decreases with increasing lag between the onset of taste- and health-information processing.

Since several alternative mechanisms are likely to be at work in dietary self-control (Baumeister & Vohs, 2004; Beaver et al., 2006; Hare et al., 2009; Harris, Hare, & Rangel, 2013; Hutcherson, Plassmann, Gross, & Rangel, 2012; Ikeda et al., 2010; Loewenstein, 1996; Muraven & Baumeister, 2000), we were surprised to find that between 13% and 39% of observed individual differences in self-control ability could be explained by differences in the relative speed with which tastiness and healthfulness are processed. By comparison, previous studies have found that personality traits such as impulsivity or IQ can explain only around 13% and 5%, respectively, of individual differences in self-control (de Wit, Flory, Acheson, McCloskey, & Manuck, 2007; Mitchell, 1999; Shamosh & Gray, 2008; Steinberg et al., 2009).

Our results are consistent with basic ideas from a wide class of integrator models of decision making, including decision-field theory; the drift-diffusion model; and the leaky, competing-accumulator model. Despite technical differences, in all of these models, decisions are made by dynamically integrating information for and against the different options (Bogacz, 2007; Rangel & Clithero, 2013). At every instant during the choice process, the decision circuitry receives instantaneous information about the attributes associated with each stimulus under consideration and integrates them into a dynamic value signal that measures the relative value of the two options. A decision is made when the relative-value signal becomes sufficiently large or sufficiently small. These models are an important benchmark for understanding self-control because they have been shown to account, with high quantitative accuracy, for psychometric choice data. Notably, they predict that the earlier an attribute is processed, the longer it is integrated into the relative-value measure, and thus the larger the weight that the attribute receives in the final decision. Thus, these models provide computational foundations for our findings.

Our study borrows heavily from the pioneering mouse-tracking literature, which has been used to study intertemporal choice (Dshemuchadse et al., 2013), visual search (Song & Nakayama, 2008), stereotyping (Freeman & Ambady, 2009), and psycholinguistics (Spivey et al., 2005). However, we used the mouse-tracking data in a different way. Whereas most mouse-tracking studies focus on comparisons between the average paths generated by various experimental conditions, we used regression analyses to identify the time at which different stimulus attributes begin influencing choice. (See Dshemuchadse et al., 2013; Scherbaum, Dshemuchadse, Fischer, & Goschke, 2010; Scherbaum, Dshemuchadse, Leiberg, & Goschke, 2013, for related uses of mouse-tracking data.)

Our study also suggests a potential mechanism by which the difficulty and abstractness of attributes may influence the choice process (Liberman & Trope, 2008). Rather than simply resulting in a weaker representation of attributes such as healthfulness, as is sometimes assumed, the abstractness of attributes might also affect the speed with which they are processed. One limitation of our study is that we cannot disentangle the influence that processing difficulty and processing speed have on self-control. In fact, it is possible that, in some contexts, both effects might be correlated. Future work will be needed to tease apart the relative roles of these two mechanisms.

Several implications of these findings merit future investigation. First, these data suggest that slowing down decisions, even if only by adding a waiting period before choice, might increase the relative influence of abstract attributes such as healthfulness on final choice. To see why, note that at longer decision times, there is a decrease in the fraction of time during which only the tastiness attribute is computed. Indeed, there is already a literature suggesting the influence of time pressure on choice (e.g., Reutskaja, Nagel, Camerer, & Rangel, 2011; Suter & Hertwig, 2011). Second, our results suggest that self-control could be improved by interventions that increase the relative speed with which health information is processed. Consistent with this, a previous study showed that simply cuing subjects to pay attention to healthfulness can improve dietary self-control (Hare, Malmaud, & Rangel, 2011). Third, these findings provide a rationale for regulating marketing practices that increase the relative ease with which abstract attributes such as healthfulness are processed. For example, prominently displaying health information (e.g., calorie counts) may allow more rapid integration of healthfulness attributes.

The fourth reason these findings merit future investigation is that they provide a potential mechanism through which differences in cognitive abilities might affect self-control. For example, individuals with higher IQ might be relatively faster at processing abstract attributes, such as healthfulness, which increases their self-control. Fifth, the relative speed of attribute processing might also play a role in other types of decisions in which basic and abstract information need to be combined. Potential examples include altruism, in which information about the self might be calculated faster than information about others, and any decision involving discounting, in which information about immediate rewards might be processed earlier than information about future rewards.

Author Contributions

All authors participated in designing the study and writing the manuscript. N. Sullivan collected and analyzed the data.

Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

Funding

Financial support for this study was provided by the National Science Foundation (NSF; AR3.SELFCNTRL-1-NSF.ARR1) to A. Rangel, the NSF Integrative Graduate Education and Research Traineeship program to N. Sullivan, the National Institute on Aging (R21-AG038866-01) to N. Sullivan and A. Rangel, and the Lipper Foundation.

Supplemental Material

Additional supporting information can be found at http://pss.sagepub.com/content/by/supplemental-data

Open Practices

All data and materials have been made publicly available via Open Science Framework and can be accessed at https://osf.io/jmiwn/. The complete Open Practices Disclosure for this article can be found at http://pss.sagepub.com/content/by/supplemental-data. This article has received badges for Open Data and Open Materials. More information about the Open Practices badges can be found at https://osf.io/tvyxz/wiki/view/ and http://pss.sagepub.com/content/25/1/3.full.

References

Ashby, F. G. (1983). A biased random walk model for two choice reaction times. *Journal of Mathematical Psychology*, *27*, 277–297.

Baumeister, R. F., & Vohs, K. D. (Eds.). (2004). *Handbook of self-regulation: Research, theory, and applications*. New York, NY: Guilford Press.

Beaver, J. D., Lawrence, A. D., van Ditzhuijzen, J., Davis, M. H., Woods, A., & Calder, A. J. (2006). Individual differences in reward drive predict neural responses to images of food. *The Journal of Neuroscience*, *26*, 5160–5166.

Bogacz, R. (2007). Optimal decision-making theories: Linking neurobiology with behaviour. *Trends in Cognitive Sciences*, *11*, 118–125.

Brainard, D. H. (1997). The Psychophysics Toolbox. *Spatial Vision*, *10*, 433–436.

Busemeyer, J. R., & Townsend, J. T. (1993). Decision field theory: A dynamic-cognitive approach to decision making in an uncertain environment. *Psychological Review*, *100*, 432–459.

Dale, R., Kehoe, C., & Spivey, M. J. (2007). Graded motor responses in the time course of categorizing atypical exemplars. *Memory & Cognition*, *35*, 15–28.

de Wit, H., Flory, J. D., Acheson, A., McCloskey, M., & Manuck, S. B. (2007). IQ and nonplanning impulsivity are independently associated with delay discounting in middle-aged adults. *Personality and Individual Differences*, *42*, 111–121.

Dshemuchadse, M., Scherbaum, S., & Goschke, T. (2013). How decisions emerge: Action dynamics in intertemporal decision making. *Journal of Experimental Psychology: General*, *142*, 93–100.

Freeman, J. B., & Ambady, N. (2009). Motions of the hand expose the partial and parallel activation of stereotypes. *Psychological Science*, *20*, 1183–1188.

Freeman, J. B., Ambady, N., Rule, N. O., & Johnson, K. L. (2008). Will a category cue attract you? Motor output reveals dynamic competition across person construal. *Journal of Experimental Psychology: General*, *137*, 673–690.

Hare, T. A., Camerer, C. F., & Rangel, A. (2009). Self-control in decision-making involves modulation of the vmPFC valuation system. *Science*, *324*, 646–648.

Hare, T. A., Malmaud, J., & Rangel, A. (2011). Focusing attention on the health aspects of foods changes value signals in vmPFC and improves dietary choice. *The Journal of Neuroscience*, *31*, 11077–11087.

Harris, A., Hare, T., & Rangel, A. (2013). Temporally dissociable mechanisms of self-control: Early attentional filtering versus late value modulation. *The Journal of Neuroscience*, *33*, 18917–18931.

Hutcherson, C. A., Plassmann, H., Gross, J. J., & Rangel, A. (2012). Cognitive regulation during decision making shifts behavioral control between ventromedial and dorsolateral prefrontal value systems. *The Journal of Neuroscience*, *32*, 13543–13554.

Ikeda, S., Kang, M.-I., & Ohtake, F. (2010). Hyperbolic discounting, the sign effect, and the body mass index. *Journal of Health Economics*, *29*, 268–284.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *The Quarterly Journal of Economics*, *112*, 443–478.

Liberman, N., & Trope, Y. (2008). The psychology of transcending the here and now. *Science*, *322*, 1201–1205.

Loewenstein, G. (1996). Out of control: Visceral influences on behavior. *Organizational Behavior and Human Decision Processes*, *65*, 272–292.

Luce, R. D. (1986). *Response times: Their role in inferring elementary mental organization*. Oxford, England: Oxford University Press.

McKinstry, C., Dale, R., & Spivey, M. J. (2008). Action dynamics reveal parallel competition in decision making. *Psychological Science*, *19*, 22–24.

Milosavljevic, M., Malmaud, J., Huth, A., Koch, C., & Rangel, A. (2010). The drift diffusion model can account for the accuracy and reaction time of value-based choices under high and low time pressure. *Judgment and Decision Making*, *5*, 437–449.

Mitchell, S. H. (1999). Measures of impulsivity in cigarette smokers and non-smokers. *Psychopharmacology*, *146*, 455–464.

Muraven, M., & Baumeister, R. F. (2000). Self-regulation and depletion of limited resources: Does self-control resemble a muscle? *Psychological Bulletin*, *126*, 247–259.

O'Donoghue, T., & Rabin, M. (1999). Doing it now or later. *The American Economic Review*, *89*, 103–124.

Rangel, A. (2013). Regulation of dietary choice by the decision-making circuitry. *Nature Neuroscience*, *16*, 1717–1724.

Rangel, A., & Clithero, J. A. (2013). The computation of stimulus values in simple choice. In P. W. Glimcher & E. Fehr (Eds.), *Neuroeconomics: Decision making and the brain* (2nd ed.; pp. 125–148). London, England: Academic Press.

Ratcliff, R., & McKoon, G. (2008). The diffusion decision model: Theory and data for two-choice decision tasks. *Neural Computation*, *20*, 873–922.

Ratcliff, R., & Rouder, J. N. (1998). Modeling response times for two-choice decisions. *Psychological Science*, *9*, 347–356.

Reutskaja, E., Nagel, R., Camerer, C. F., & Rangel, A. (2011). Search dynamics in consumer choice under time pressure: An eye-tracking study. *The American Economic Review*, *101*, 900–926.

Rolls, E. T., Grabenhorst, F., & Deco, G. (2010). Choice, difficulty, and confidence in the brain. *NeuroImage*, *53*, 694–706.

Scherbaum, S., Dshemuchadse, M., Fischer, R., & Goschke, T. (2010). How decisions evolve: The temporal dynamics of action selection. *Cognition*, *115*, 407–416.

Scherbaum, S., Dshemuchadse, M., & Goschke, T. (2012). Building a bridge into the future: Dynamic connectionist modeling as an integrative tool for research on intertemporal choice. *Frontiers in Psychology*, *3*, Article 514. Retrieved from http://journal.frontiersin.org/Journal/10.3389/fpsyg.2012.00514/full

Scherbaum, S., Dshemuchadse, M., Leiberg, S., & Goschke, T. (2013). Harder than expected: Increased conflict in clearly disadvantageous delayed choices in a computer game. *PLoS ONE*, *8*(11), Article e79310. Retrieved from http://www.plosone.org/article/info%3Adoi%2F10.1371%2Fjournal.pone.0079310

Shamosh, N. A., & Gray, J. R. (2008). Delay discounting and intelligence: A meta-analysis. *Intelligence*, *36*, 289–305.

Song, J.-H., & Nakayama, K. (2008). Target selection in visual search as revealed by movement trajectories. *Vision Research*, *48*, 853–861.

Spivey, M. J., Grosjean, M., & Knoblich, G. (2005). Continuous attraction toward phonological competitors. *Proceedings of the National Academy of Sciences, USA*, *102*, 10393–10398.

Steinberg, L., Graham, S., O'Brien, L., Woolard, J., Cauffman, E., & Banich, M. (2009). Age differences in future orientation and delay discounting. *Child Development*, *80*, 28–44.

Suter, R. S., & Hertwig, R. (2011). Time and moral judgment. *Cognition*, *119*, 454–458.

Usher, M., & McClelland, J. L. (2001). The time course of perceptual choice: The leaky, competing accumulator model. *Psychological Review*, *108*, 550–592.