Dietary self-control depends on the latency and rate of information accumulation

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Abstract

The drift diffusion model (DDM) provides a parsimonious explanation of decisions across neurobiological, psychological, and behavioral levels of analysis. Although most DDM implementations assume only one type of information guides decisions, choices often involve multiple attributes that may have differential effects. Here, we fit incentive-compatible dietary choices to a multi-attribute, time-dependent, drift diffusion model (mtDDM), in which taste and health independently influenced the relative value signal that drives the accumulation process in a manner consistent with participants' idiosyncratic preferences. Health information entered the decision process after a longer latency than taste information, diminishing the likelihood of healthy choices. Finally, by using a dietary prime, we showed that variation in mtDDM parameters followed interindividual variation in observed behavior. Our results show that different decision attributes make separable contributions to the timing and strength of evidence accumulation – and thus provide new insights into the construction of interventions that may shape the choice process.

Dietary choices often involve conflicts between contradictory desires, such as short-term goals related to consumption of a tasty snack and long-term goals related to personal health. Such choices are often considered to be challenging because of a difficulty in exerting self-control when negative health outcomes are distant in the future[1]. Furthermore, because interventions directed at improving dietary self-control have found limited success, it is critical to identify the mechanisms of dietary choice – particularly if healthy choices might depend on something other than self-control[2-5].

Simple choices, including between food items, have been characterized using sequential integrator models such as the drift diffusion model (DDM)[6-9]. In the DDM, binary choices are made by dynamically integrating evidence for and against each option over time – and a decision is made when the evidence signal reaches the threshold associated with one of the choice options. A key advantage of these models is their ability to dissociate the influences of multiple distinct cognitive processes on choice, such as distinguishing bias toward one choice option from a reduced threshold for evidence before making a decision. Although current iterations of these models provide highly accurate descriptions of the psychometrics of value-based choices (i.e., they describe both choices and their response times in laboratory experiments), they do not account for important potential contributors to the choice process, including potentially distinct contributions of different attributes to a single choice[10,11].

Here, we present a multi-attribute, time-dependent, drift diffusion model (mtDDM; Fig. 1) that modifies the traditional DDM in two ways. First, it estimates the rate of evidence accumulation at each time point ("*drift slope*") separately for two key attributes (here, tastiness and healthfulness of a snack food). Modeling separate attribute drift slopes allows estimation of their independent contributions to the value signal while controlling for other features of the decision process[12,13]. Second, the mtDDM allows taste and health information to begin influencing the option comparison process at different times ("*drift latency*"). Thus, the mtDDM allows us to measure the independent contributions to dietary self-control of the weight placed on taste and health in the decision process as well as the *time* at which each attribute begins to influence this process. This latter parameter has been found to vary by attribute, and therefore could have differential effects when controlling for drift slopes.

We tested the robustness of the mtDDM within an incentive-compatible experiment in which participants made a series of binary choices between two foods that varied on two key attributes: their tastiness and healthfulness. A behavioral prime was also employed to shape participants' dietary goals via attention to these health or taste attributes. By focusing attention to each attribute in independent participant groups, we perturb the decision process, and thus can evaluate how well the mtDDM can adapt to changes in attribute weighting. Because drift slopes have been shown to vary depending on allocation of attention[14], an intervention that successfully increases attention to one attribute could increase its rate of accumulation and therefore bias choice – independently of any effects of self-control. We hypothesize that increased focus on the primed attribute may also facilitate faster processing of that attribute, and that these speeded latencies could help to facilitate more health-focused choices.

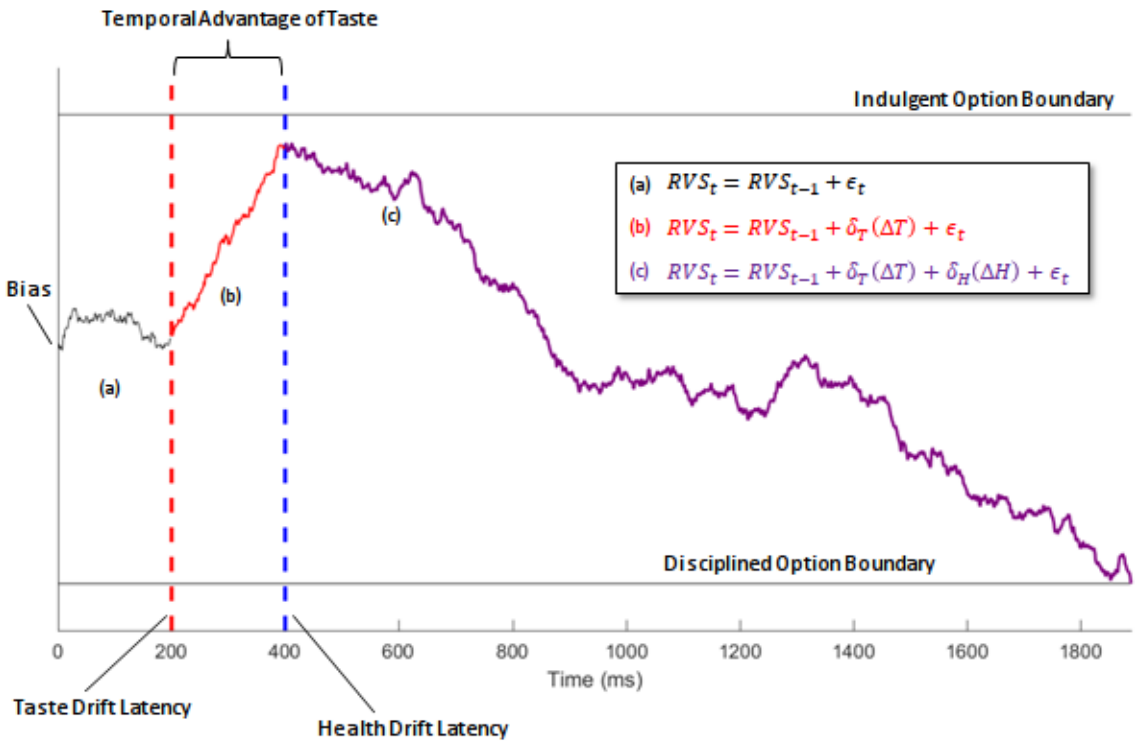

Figure 1 | Example of the decision process modeling within the multi-attribute, time-dependent drift diffusion model (mtDDM). In this example choice between an indulgent food (tasty but unhealthy) and a disciplined food (healthy but not tasty), a relative value signal (RVS) begins with a value set by a bias parameter (here, set to zero) and evolves only with noise, ε, at every timepoint t as depicted in equation and segment "a". Once the taste attribute's latency is reached (red dotted line), the relative (indulgent – disciplined) taste value, ΔT, begins contributing to the RVS at a rate determined by its drift slope δ_T (segment "b"). After the health attribute latency is reached (segment "c"), relative health value, ΔH, also begins contributing to the RVS at a rate determined by its drift slope δ_H. At each time point, Gaussian noise ε is added to the value signal. A decision is said to be reached when the RVS becomes equal to or greater than the boundary for an item. In this example, the taste attribute has a "temporal advantage" (i.e., it begins contributing to the RVS first), and thus the indulgent option boundary is nearly crossed before the health attribute begins contributing toward the eventual disciplined choice. In the example decision process depicted here, a simulated RVS path is displayed for a choice in which the difference in taste and health attributes are $\Delta T = 1$ and $\Delta H = -7$, and mtDDM parameters are set to $\delta_T = 0.005$ units/ms, $\delta_H = 0.0009$ units/ms, $t^*_T = 200$ ms, $t^*_H = 400$ ms, bias = 0, and indulgent option boundary = 1 and disciplined option boundary = -1. Figure adapted from[15].

Results

Simulation of the mtDDM. First, we generated simulated mtDDM data to derive qualitative predictions for how our key new parameters – specifically, the relative taste and health latencies – influence both response times and disciplined choices. The simulations were performed using an artificial choice set comprising foods with health and taste values like those in the experimental dataset (see below sections for details on the experiment, and Supplemental Methods for simulation methods).

In the simulations, the relative latency of health information compared to taste information was varied, but all other parameters of the mtDDM were held constant. Critically, the drift slopes were taste and health – which parameterize the weight placed on each attribute during option comparison – were held to be equal. For each trial, 1,000 choices were simulated, and proportion of disciplined choices and mean response times were recorded. We found that as health latencies became faster, there was an increase in the proportion of disciplined choices as a function of value (in this simulation, value was the unweighted sum of taste and health), as evidenced by a leftward shift in the psychometric choice curve (Fig. 2a, in blue). Conversely, the psychometric curve

shifts to the right as health latencies became slower (in red), which would instead lead to indulgent choices. The simulations also predict a pattern in response times that would be expected from value-based choices: specifically, that response times will be longer when both options are similar in value (Fig. 2b).

Figure 2c displays the disciplined choices predicted by the mtDDM simulation in a different way. It illustrates the proportion of disciplined choices predicted as health latencies became faster than (to the left of the grey bar) or slower than (to the right of the grey bar) the taste latency, which was always fixed to 200 ms (grey bar). As health's latency became earlier, the disciplined option was selected more often - even when the value of the disciplined item was much worse than the indulgent item (bottom left, in blue). Disciplined choices declined as health's latency became increasingly slower than taste's latency. This further illustrates that earlier health latencies predict more disciplined choices, even in cases in which the tempting indulgent item was higher in value.

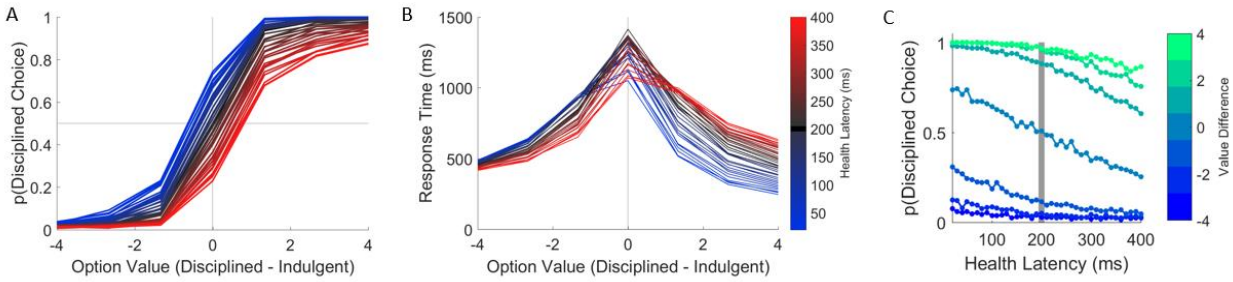

Figure 2 | Simulation results. (**a**) The proportion of disciplined choices for each value difference (Disciplined– Indulgent Food Value) are plotted for different relative latencies. Darker lines represent more similar latencies. Blue lines represent earlier health than taste latencies, and red lines represent earlier taste than health latencies. (**b**) Mean response times for each value difference (Disciplined– Indulgent Food Value) are plotted for different relative latencies; line colors are similar to those in the previous panel. (**c**) The proportion of disciplined choices (y-axis) predicted as a function of health latency (y-axis) and option value difference (green to blue). When taste and health's latencies are equal (at 200 ms, indicated by the grey bar), both attributes entered the decision process at the same time. Value differences, indicated here by colors green to blue, represent the relative (Disciplined – Indulgent) value (taste + health) of the options, with green representing a higher valued disciplined option and blue representing a higher valued indulgent option. As the disciplined option increased in value (green), it was selected more often. There was a further increase in disciplined choices moving from the grey bar to the left, indicating faster health latencies relative to taste latencies. Conversely, as health latencies became slower, plotted here to the right of the grey bar, fewer disciplined choices were made.

Behavioral Results. We performed several tests to ensure that participants were choosing according to their preferences in both health and taste prime conditions and that their behavior fit expected patterns of response times. We found that choices were significantly related to wanting for both the health and taste primed participants (Fig. 3b; mixed effects slope: health prime M = 1.02, d = 1.82, t_{39} = 11.53, $p < 1\text{x}10^{-10}$; taste prime M = 1.35, d = 2.33, t_{38} = 14.57, $p < 1\text{x}10^{-10}$). Logistic slopes were significantly smaller in health-primed participants (d = -0.59, t_{77} = -2.61, p = 0.01). Response times (RTs) increased with choice difficulty for both groups (Fig. 3c; mixed effects quadratic slope: health prime M = -45.30, d = -1.41, t_{39} = -8.90, $p < 1\text{x}10^{-10}$; taste prime M = -40.34, d = -1.86, t_{38} = -11.62, $p < 1\text{x}10^{-10}$). Quadratic slopes were not significantly different between the taste than health prime (d = -0.18, t_{77} = -0.80, p = 0.43), and average response times themselves were not different by condition (means 1628 vs. 1554 ms, d = 0.13, t_{77} = 0.59, p = 0.56). These results indicate that individuals used value information to guide choice in both

conditions, and that health-primed participants weighted wanting value information less in their choices than taste-primed participants.

We next estimated the influence of our behavioral prime on choice using a mixed-effects logistic regression on choice using each food's taste and health differences, to estimate the weight each participant placed on taste and health information in choice, and how this changed depending on the prime they received. We found that health-primed participants placed significantly less weight on taste information (Fig. 3d; means 1.18 vs. 0.13, d = 2.24, t_{77} = 9.94, $p < 1\text{x}10^{-10}$), which resulted in a marginal increase in the proportion of disciplined choices in the health prime condition, as assessed by comparing their log-transformed values (means = 0.26, 0.18; d = 0.44, t(75) = 1.94, 95% CI = [-0.01 0.83], p = 0.057).

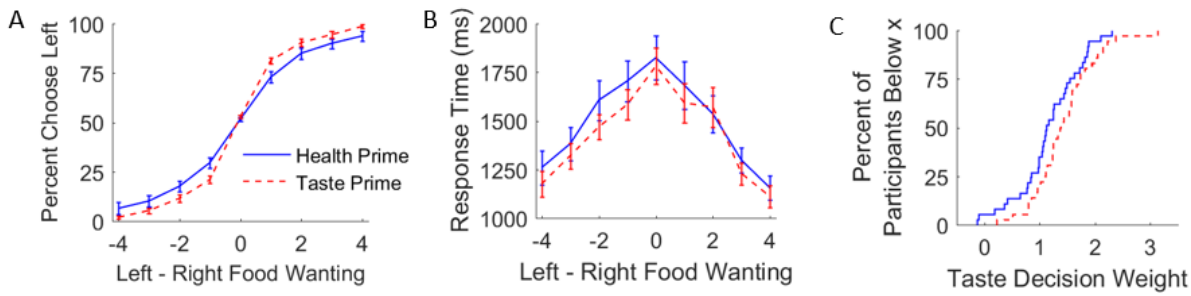

Figure 3 | Behavioral results. (**a**) The proportion of left-hand choices for each value difference (Left – Right Food Wanting) are plotted for the health (blue solid line) and taste (red dotted line) prime conditions. (**b**) Mean response time (RT) is shown as a function of choice difficulty for the health (blue solid line) and taste (red dotted line) prime conditions, as measured by the difference between wanting for the right item and for the left item. A value difference of zero indicates a difficult choice between two equally-wanted options, and a 4 or -4 indicates an easy choice between options with opposite value. (**c**) Cumulative distribution function illustrating taste decision weights by prime condition broken out by whether the participant was primed for health (blue) or taste (red) goals. For plots A and B, error bars represent standard error of the mean.

Fitted parameters of the mtDDM. Using participants' choices and response times, we fit five mtDDM parameters. These parameters were the weight placed on taste and health during option comparison ("drift slope", δ_T and δ_H), the time required for taste and health to enter option comparison ("drift latency", t^*_T and t^*_H), and the amount of evidence required to make a choice ("Boundary", b). The average best-fitting diffusion parameters are reported in Table 1 (see Fig. S2 for parameter distributions). Taste drift slopes, δ_T, were significantly larger than health drift slopes, δ_H (d = 1.60, t_{78} = 10.28, $p < 1\text{x } 10^{-10}$), reflecting an overall greater emphasis on taste information in evidence accumulation. Of note, the best-fitting health drift slope was zero for one participant, meaning that this individual did not use health information to guide the option comparison process. Drift latency was significantly earlier for taste, t^*_T, than for health, t^*_H (d = -0.99, t_{78} = -5.78, $p = 1\text{x}10^{-7}$), which held when excluding the participant whose best-fitting health drift slope was zero (d = -0.98, t_{77} = -5.70, $p = 2\text{x}10^{-7}$).

Table 1 | Average best-fitting mtDDM parameters.

	Mean (SD)	Min	Max
δ_T (units/ms)	0.04 (0.02)	0.01	0.12
δ_H (units/ms)	0.01 (0.01)	0	0.06
t^*_T (ms)	186 (284)	10	1740
t^*_H (ms)	597 (516)	10	1730

b (units)	1.24 (0.20)	0.88	1.88

As further evidence for the viability of our multi-attribute model, there was no correlation between taste and health drift slopes (ρ = 0.06, p = 0.61) nor between taste and health drift latencies (ρ = -0.17, p = 0.13). In an additional step, we estimated the relationship between each attribute's drift slope and each attribute's drift latency (see Fig. S3). We find that taste drift slopes and latencies were not correlated (ρ = 0.05, p = 0.67), but that health drift slopes and latencies were marginally correlated (ρ = -0.21, p = 0.06).

We next examined the boundary width, which typically has been linked to response caution[16-20], although see[21] for a different perspective. Boundary width was not related to health drift slopes or taste drift latencies (p > 0.12). However, larger boundary width was correlated with smaller taste drift slopes and with later health drift latencies (δ_T, ρ = -0.30, p = 0.01; t^*_H, ρ = 0.27, p = 0.02). This indicates that individuals who process health information later – or who had a smaller contribution of taste information during evidence accumulation – required more evidence to make a choice. This larger boundary width may allow some individuals to compensate for a late health drift latency and still make a healthy choice – a hypothesis we investigate in the penultimate section of these Results.

Together, these results indicated that taste information has two advantages during the decision process – both an earlier entry and a greater contribution to evidence accumulation – that together explained its greater influence on the relative value signal and subsequent decisions. We next assessed whether variability in model parameters associated with health and taste can account for differences across individuals in healthy choices, such that effects usually attributed to self-control could be instead linked to computational advantages during the choice process.

Simulation: mtDDM parameters predict observed healthy choices. We next performed a second test of the mtDDM using simulated choices to assess whether the attribute latency parameter improved prediction of disciplined choices made by participants during the experiment. In this test, we predicted the proportion of disciplined choices a participant would make given their fitted mtDDM parameters and the options experienced on each trial in the experimental task. For each real experienced trial, choices and response times were estimated (see Methods for procedures). This was done twice: once assuming that taste and health entered the diffusion process at the times specified by their estimated latencies, and again assuming that taste and health entered at the same time (the faster of the two estimated latencies). Predicted and observed disciplined choices were highly correlated (Fig. S4a; Pearson $\rho = 0.93$, $p < 1x10^{-10}$) when allowing latencies to vary according to their individual fitted values. Although predicted disciplined choices were also highly correlated with observed responses when assuming health and taste latencies were equal, the correlation was weaker (Fig. S4b; Pearson $\rho = 0.87$, $p < 1x10^{-10}$).

This comparison between predicted and actual disciplined choices suggests two major points: one, that the mtDDM predicts the proportion of disciplined choices participants made; two, accounting for health and taste's attribute latencies provides a better overall prediction of disciplined choices than a model without these parameters.

Attribute drift slopes are proportional to their influences on choice. Because drift slope represents the weight placed on an attribute at each time step, an attribute's drift slope should be highly correlated with its weight in choice. To test this, we estimated the relationship between

taste and health drift slopes and their decision weights using a linear regression. As predicted, we found that larger drift slopes were linearly related to larger decision weights for both taste and health (Fig. 4a; taste, R^2 = 0.26, slope = 12.98, p = 2x10^{-6}; health, R^2 = 0.34, slope = 22.31, p = 2x10^{-8}). As a second test, we hypothesized that the proportion of healthy choices made by a participant in *conflict trials* (trials in which one food was healthier, but less tasty, than the other; see Methods for details) should be partially predicted by smaller taste, and larger, health drift slopes. Indeed, we found that smaller taste drift slopes and larger health drift slopes were associated with a greater proportion of healthy choices on those trials (taste, R^2 = 0.22, slope = -4.33, p = 2x10^{-5}; health, R^2 = 0.24, slope = 9.14, p = 5x10^{-6}).

Taste and health drift latencies related to their weight in choice. We hypothesized that an attribute that entered the decision process earlier would have a greater influence on choice, because their influence on the relative value signal accumulates for longer. To test this, we first used linear regressions to estimate the relationship between each attribute's drift latency and its weight in choice, as estimated by logistic regression. We find that earlier drift latencies were correlated with larger decision weights for both taste and health (Fig. 4b; taste, R^2 = 0.17, slope = -0.0008, p = 0.0002; health, R^2 = 0.16, slope = -0.0003, p = 0.0002).

Next, we estimated the relationship between drift latency and healthy choices. We find that later taste drift latency times were related to more healthy choices (Fig. 4d; R^2 = 0.24, slope = 0.0004, p = 6x10^{-6}), and earlier health latencies were related to more healthy choices (R^2 = 0.14, slope = -0.0001, p = 0.0007). These results indicate that the influence of taste and health on choice depends on the time at which each attribute began to influence the decision process.

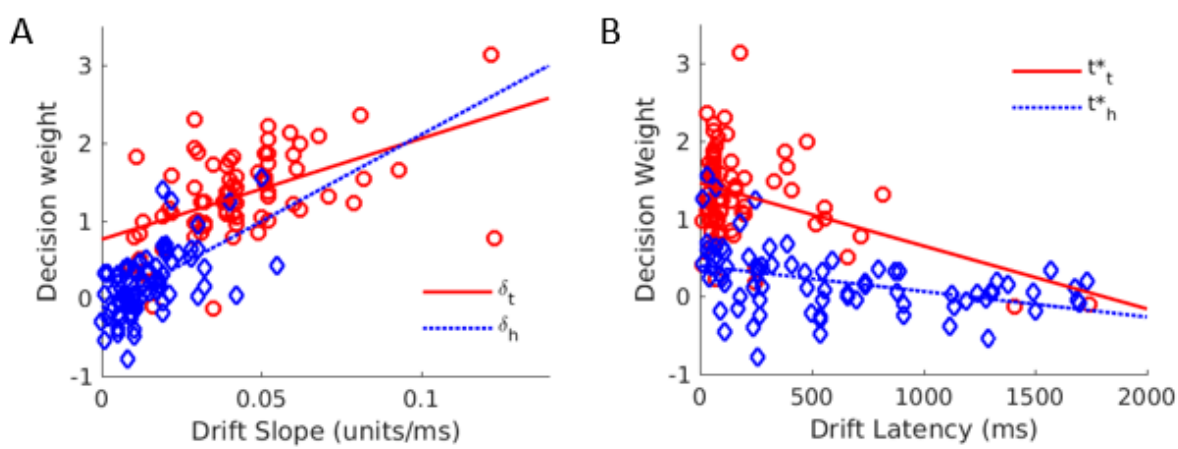

Figure 4 | Attribute drift parameters related to decision weights. (**a**) Drift slopes plotted as a function of their logistic choice decision weights. (**b**) Taste and health drift latency shown as a function of their logistic decision weights. Lines represent best-fitting linear regression lines.

Taste's weighting advantage associated with individual dietary self-control. An individual's ability to make healthy choices was, in part, determined by the relative emphasis placed on taste, compared to health, information in their choices. Therefore, we hypothesized that a participant's *relative* drift slope (taste – health) would be related to healthy choices. We assess this in two ways. First, assessed the correlation between a participant's relative weight on taste compared to health during choice (taste – health weights), as assessed by logistic regression, and their relative drift slopes. We found that larger drift slopes for taste, relative to health, were associated with larger weights on taste, relative to health, in choice (R^2 = 0.48, slope = 0.24, p < 1x10^{-10}).

Second, we expected and found that larger health, relative to taste, drift slopes were associated with a greater proportion of healthy choices (Fig. 5a; $R^2 = 0.43$, slope = -0.06, $p < 1\text{x}10^{-10}$), and explain more variance in healthy choice than either attribute's drift slope independently (22% and 26% for taste and health respectively). Together, these results indicate that an attribute's drift slope was highly correlated with its influence on choice, which allows this parameter to capture a large proportion of the variance in dietary self-control.

Healthy choice reflects a *relatively* early entry of health information. We hypothesized that although drift latencies might independently predict healthy choice when examined in isolation, stronger predictions should come from examining an attribute's *temporal advantage*: the additional time the faster-calculated attribute has in which to influence the decision process. To estimate each attribute's temporal advantage in the decision process, we calculated the difference between taste and health drift latencies. Positive numbers represented a temporal advantage for health information, and negative numbers meant that taste had a temporal advantage in the option comparison process.

Across participants, we found that the temporal advantage for the processing of health information was related both to an increased decision weight on health, relative to taste (health – taste logistic weights; $R^2 = 0.23$, slope = 0.0006, $p = 9\text{x}10^{-6}$) and thus more healthy choices (Fig. 5b; $R^2 = 0.27$, slope = $2\text{x}10^{-6}$, $p = 1\text{x}10^{-6}$). Because of outliers visible in this figure, we used a robust regression approach to confirm that this relationship held even when excluding extreme data points (slope = $6\text{x}10^{-7}$, $p = .015$). Importantly, as with drift slopes, the temporal advantage metric explains more variance in dietary choice than either taste or health latency alone (24% and 14%, respectively). These results provide an additional explanation for apparent failures of dietary self-control: for many individuals, health information enters the decision process too late (relative to taste information) to drive choices toward the healthier option.

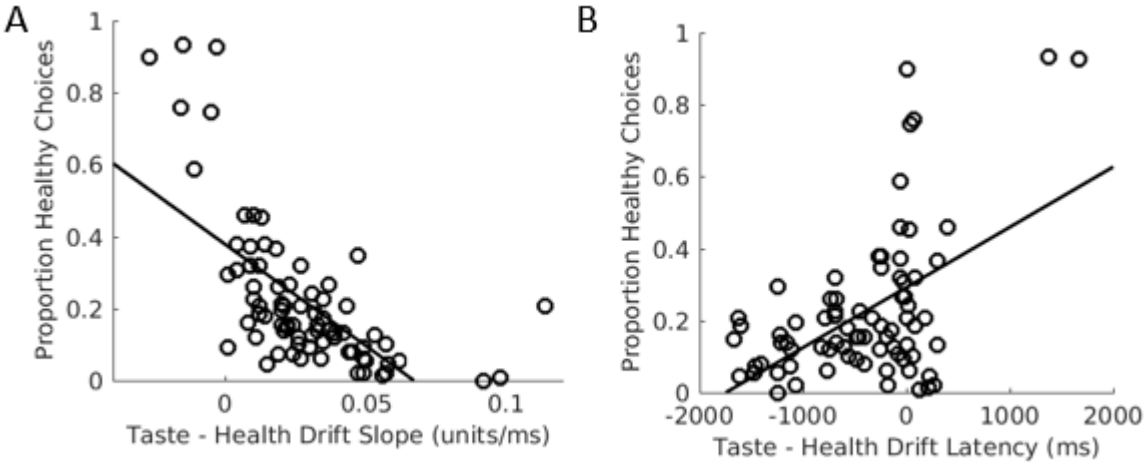

Figure 5 | Taste's decision advantage and healthy choices. (**a**) Relative drift slope (taste – health) plotted against proportion healthy choices. (**b**) Relative (taste – health) drift latency shown as a function of proportion of healthy choices. Lines represent best-fitting linear regression lines.

Drift slope and attribute latency have independent influences on healthy choice. We had hypothesized that drift slope and latency exert independent influences on choice, even when controlling for the effect of each other. To test this, we estimated a series of multiple linear regressions using drift slope and latency to predict the proportion of healthy choices made (Table

2). To control for response caution, boundary width was also included. As expected, drift slopes and latencies alone predicted individual differences in proportion of healthy choices. All mtDDM variables together explained a much larger proportion of the variance in healthy choices, at 68%, than any other model alone (Model 4 in Table 2). Of note, boundary width was not significantly related to healthy choices either alone, or in a model with other mtDDM variables. A model of relative (taste – health) drift slopes and latencies was also tested and had slightly less explanatory power (70% vs. 65%; *see* Supplementary Table S1).

In a further step, we performed a bootstrap mediation analysis[22] to estimate the additional contribution of drift latency to the proportion of healthy choices. Health drift latency significantly reduced the health drift slope's influence on healthy choices decision weights by 12% (s.e. = .30, 5% CI = [11.73 12.90], $p < 1x10^{-10}$). There was a similar but smaller reduction in taste drift slope's prediction of healthy choices by taste drift latency (2%; s.e. = .50, 5% CI = [0.58 2.5], p = .002). Together, these results indicated that healthy dietary choice was related to both the drift slope and latency parameters of the mtDDM, even when controlling for the effects of each other, reflecting their independent contributions to choices.

Table 2 | Relationship between proportion healthy choices and fitted mtDDM parameters.

	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**
δ_T	-0.05***			-0.05***
	(-6.11)			(-7.44)
δ_H	0.01***			0.08***
	(6.42)			(6.18)
t^*_T		$3x10^{-6}$***		$3x10^{-6}$***
		(4.37)		(5.45)
t^*_H		$-1x10^{-6}$**		$-1x10^{-6}$**
		(-2.91)		(-3.50)
Bounds			0.02	0.03
			(0.19)	(0.47)
Constant	0.28***	0.23***	0.20	0.27**
	(6.73)	(6.74)	(1.34)	(2.68)
R^2	0.49	0.32	$1x10^{-3}$	0.70
R^2_{adj}	0.48	0.30	0	0.68
t-statistic in parentheses				
***p<.05 **p<.01 ***p<.001**				

Longer response times associated with greater influence of health. The above findings suggest that longer response times (RTs) could be associated with an increased likelihood of selecting the healthier option, as longer RTs would allow slower-processed values like healthfulness more time to contribute to the value signal. To test this hypothesis, we used a mixed-effects logistic regression to estimate the relationship between individual trial RT and likelihood of a healthy choice in conflict trials (in which one food was tastier, and less healthy, than the other). We found that longer RTs were associated with an increased likelihood of selecting the healthier, less tasty food (Table S2, Model 1; mixed-effects logistic regression R^2_{adj} = .37, log(RT) slope = 0.61 (s.e. = 0.05), t_{11698} = 11.85, $p < 1x10^{-10}$), which holds when controlling for the reported wanting of the disciplined, relative to indulgent, option (Table S2, Model 2; $p = 1x10^{-8}$). To assess whether this RT relationship held across participants as well, we also estimated this regression using average log-transformed conflict trial RTs to predict the proportion of healthy choices made and found the same relationship (robust regression slope = 0.09, t_{76} = 2.01, p = 0.048). This regression was not significant when using non-conflict response times to predict the proportion of healthy choices (slope = 0.03, t_{76} = 0.56, p = 0.58). Of note, there were no log(RT) differences between prime groups in these conflict trials (p = .81) or for all other trials (p = .94). This suggests that longer

RTs were correlated with increased likelihood of healthy choices both within and across participants.

Next, we assessed whether this varies depending on a participant's mtDDM parameters. If longer RTs promoted healthy choices because they allowed slower-processed health information longer to influence the decision process, then individuals with faster health latencies would have been less influenced by longer response times. To investigate this, we first added health drift latency (t^*_H) to the previous model predicting healthy choice by response time. Response times, however, remained a significant predictor of healthy choice (Table S2, Model 3; mixed-effects logistic regression, $R^2 = 0.52$, log(RT) slope = 0.37 (s.e. = .05), $t_{11696} = 7.17$, $p < 1\text{x}10^{-10}$; wanting slope = 0.93 (s.e. = 0.07), $t_{11696} = 13.61$, $p < 1\text{x}10^{-10}$; t^*_H slope = $-1\text{x}10^{-5}$ (s.e. = $3\text{x}10^{-6}$), $t_{11696} = -3.99$, $p = 7\text{x}10^{-5}$). This indicated that even after controlling for the weight of health and taste in the decision process, response times continued to explain additional variance in an individual's ability to exert dietary self-control.

To assess the interplay between the influence of latency and response time, we added interaction terms for response times and health drift latency. If, for example, slower health drift latencies require longer response times to increase the likelihood of a healthy choice, we would see a significant interaction between health drift latency and response time. We indeed find that the influence of drift latencies on healthy choice depended on a trial's response time. Specifically, longer response times were associated with increased likelihood of a healthy choices when health drift latencies were slow. Further, response time's predictive power was reduced by a third and was no longer significant when drift latency-response time interactions were included in the regression (Table S2, Model 4; mixed-effects logistic regression, $R^2 = 0.51$, log(RT) slope = 0.11 (s.e. = 0.08), $t_{11695} = 1.36$, $p = 0.17$; wanting slope = 0.93 (s.e. = 0.07), $t_{11696} = 13.54$, $p < 1\text{x}10^{-10}$; t^*_H slope = $-4\text{x}10^{-5}$ (s.e. = $9\text{x}10^{-6}$), $t_{11695} = -4.87$, $p = 1\text{x}10^{-6}$; log(RT) x t^*_H slope = $4\text{x}10^{-6}$ (s.e. = $1\text{x}10^{-6}$), $t_{11695} = -3.81$, $p = .0001$). Together, these results support the idea that longer response times may promote health choices by allowing slower-latency health information an opportunity to contribute more to the value accumulation process, resulting in an increased likelihood of a healthy choice.

Dietary primes alter the processes of evidence accumulation. Finally, we examined the effects of our two dietary primes – a taste prime and a health prime – on the evidence-accumulation process as measured by the mtDDM. We found that log-transformed taste drift slopes were smaller for health- than taste-primed participants (Fig. S5a; means 0.04 vs. 0.05, $d = -0.40$, $t_{77} = -2.50$, $p = 0.015$). Log-transformed taste drift slopes were also relatively smaller than health drift slope for health primed participants (δ_T-δ_H; Fig. S5b; means 0.02 vs. 0.03, $d = -0.44$, $t_{77} = -2.45$, $p = 0.046$). No other parameter differed between prime conditions ($p > 0.54$). This suggests that the health prime altered the decision process by influencing the degree to which taste information influenced the value signal, both in absolute terms and relative to health information.

Discussion

Poor dietary choices are often attributed to the combination of two factors: strong preferences for the tasty foods that are endemic to modern society, and limitations in how well self-control mechanisms can inhibit the strength of those preferences[23]. Our findings support the alternative explanation that indulgent dietary choices reflect not only of relative strength of taste preferences but also their relative timing[10,11]. That is, an individual may eat a cookie not because the desire for a tasty snack overwhelms their limited willpower, but because information about future health consequences does not enter the decision process sufficiently early to influence their decision.

Hereafter, we explore the implications of our results both for models of the decision process and for understanding decision making in the face of competing goals.

Sequential integrator models such as the drift diffusion model (DDM) have been used to understand the mechanisms underlying binary choices[6,24]. One useful feature of these models is that they allow clear separation of different cognitive processes that drive choice. Here, we introduce a multi-attribute, time-dependent, DDM (mtDDM) which allows two distinct and often opposing attributes, taste and health, to be processed at different times, and weighted differently in the option comparison process. We show that both the influence of an attribute on evidence accumulation (drift slope) and the delay before an attribute contributes to the evidence accumulation process (drift latency) differ significantly by attribute – and that between-attribute differences in these two parameters explain a large proportion of the variance in dietary self-control. This indicates that models assuming that the relative value signal reflects the total stimulus value – and not potentially independent attributions – may be unnecessarily limited in their explanatory power.

Our findings have several implications. First, they generate the clear recommendation that slowing down the decision process may mitigate the effects of relative attribute latency or lower weighing of health, which could improve choices for some multi-attribute decisions. Further, this suggests a mechanistic explanation for previous work showing that the relative encoding of taste information in in value-related brain regions decreases when free response times are allowed and increases with shorter response times[25], such as time pressure[26], which has been shown to alter parameters of the DDM[27]. Future interventions to improve choice could either attempt to remove time pressure from dietary choices where they often occur, such as at a drive-through window, or attempt to extend the decision process by mandating a waiting time before choice.

Second, we find that a prime that explains the importance of healthy eating can successfully decrease the weight placed on taste information during evidence accumulation, facilitating more healthy choices. Such primes can readily be incorporated into choice architectures, allowing future work to test variations of this prime and its application outside the lab – which in turn may provide opportunities for improving choice[2].

Third, we propose that the processes identified for simple multi-attribute dietary choices should exist for other decision domains in which different types of value information may be processed differently by the brain. For example, in financial choices, one must often make a trade-off between spending money now, and saving for the future[28-30] – and, similar to what is seen for dietary choices, the future consequences of financial saving may not be as readily estimated as the immediate benefits of spending now. This may lead to a slowed estimation of the value of delayed financial rewards, and therefore more impulsive choices, regardless of an individual's underlying preference for immediate or delayed rewards.

A multi-attribute DDM model has also been proposed for social decision making[12], and adding the latency parameter could extend this work. For example, the speed with which rewards for the self and others are processed and incorporated into the decision process may increase the model's explanatory power, as well as individual differences in prosociality. Applying the mtDDM to different choice contexts, and with different forms of nudges, could help expand our understanding of both the decision process and how to improve choice.

There are multiple limitations to our mtDDM model that could be addressed in future studies. First, our model assumes that drift slopes begin at zero but transition discretely to some fixed weight following a latency period. However, many cognitive mechanisms (e.g. attention) could alter the drift slope over time. Indeed, attention has found to significantly influence the evidence accumulation process[31]. A time-variable drift rate[32] could address this by assessing whether taste and health drift slopes vary over time; for example, such a model could be implemented for

dietary choice by down-weighting the taste drift slope once health information is computed. Second, the mtDDM presented here assumes that taste and health information combine linearly to guide choice. However, non-linear utility functions are often more robust[33]. For example, in monetary decision making, a hyperbolic model is often used to combine immediate and future value information into a singular utility to guide choice [28,34,35]. Future work could probe the precise functional form appropriate for evidence accumulation in dietary choice. Third, previous work has found significant trial-to-trial variability in DDM parameters[19,36], which our technique does not account for. Future work addressing these fluctuations may help explain within-individual variability in dietary choice. Forth, the mtDDM could be adapted to handle more than two choice options; doing so would extend our procedures to accommodate more complex, multi-option choices which are closer to decisions outside the lab.

Finally, our work suggests that different interventions may work better for some individuals than others. For example, individuals with very slow processing of health information might benefit most from extending their decision process by introducing a wait time before choice. For others who weigh health minimally or not at all in choice, extending decision time may not substantially improve choice; instead, interventions would need to first encourage consideration of health information (in any form), at least relative to taste information, through a mechanism such as priming. By broadening interventions beyond appeals to self-control to include a more nuanced consideration of the timing and strength of different attributes, researchers and policy makers will be more likely to identify methods for eliciting disciplined choices.

Methods

Participants and sample size. Seventy-nine young adults from the Durham-Chapel Hill community (64% female; mean age 24.4 years) participated in this 90-minute study. Participants were screened for any dietary restrictions. Informed consent was obtained after the experiment was explained to participants.

The targeted sample size (40 individuals in each of two priming groups) was determined based on measurements in two independent datasets (results in preparation for publication) that included a binary choice task like our task described below. First, we calculated the effect of our differential priming conditions on the proportion of healthy choices across a large sample of subjects (N=133), which generated an approximate required sample size of between 40 and 45 participants in each prime group (via the sampsizepwr function in MATLAB and a $p < 0.05$ threshold for effects by prime). We next examined the robustness of our priming effects in a second independent data set (N = 40), in which the main effect of our primes fully replicated. Based on these prior results, we set 40 participants in each prime group as the target sample size in the current study.

One participant did not have sufficient variability in food ratings to generate 150 conflict trials; that participant is not included in analyses involving the proportion of healthy choices in conflict trials.

Experimental procedure. Prior to the experiment, participants fasted for four hours, with compliance as measured by computerized self-report. Participants were compensated with $12 in cash and a snack food for consumption at the end of the experiment. All stimuli were presented with the Psychophysics Toolbox [37] for MATLAB. The experiment contained four phases, always presented in the below order. See Supplemental Methods for task instructions.

Phase 1: Rating Task. Participants began by rating 30 familiar snack foods on three five-point scales. They were asked their opinions of the tastiness, healthfulness, and wanting ("How much do you want to eat this food at the end of the experiment?"). Scale type, food presentation order, and left-right scale direction (good to bad, or bad to good) were randomized across participants.

Stimuli were 600 x 600 pixel full-color images on a black background, presented alongside a one- to three-word item name (e.g. "Oreos"). Food images included a sample of the food outside of its packaging (e.g., a few chips outside the chips bag).

Phase 2: Goal Priming. Each participant was randomly assigned to one of two priming conditions. After the ratings task, participants read instructions for the following Food Choice Task (described below). A short instructional script (see Supplemental Methods) was imbedded in these instructions. This script emphasized the importance of either health information ("Health Prime"; N=40) or taste information ("Taste Prime"; N=39) in dietary choice using science-based reasoning.

Phase 3: Choice Task. Next, participants made 300 self-paced choices between pairs of foods they had rated in Phase 1. On each trial, they saw two foods and indicated which they would like to eat more using a keyboard (Fig. 4a) and were told that one trial would be randomly selected, and that food would be served to them at the end of the experiment. Using the participants' previous food ratings, half of the trials were constructed with one food that was tastier and less healthy than the other food ("Conflict Trials"). Note that one participant did not have enough variance in health and taste ratings to construct 150 conflict trials; for that participant, foods were paired randomly, and any reported statistic measuring the proportion of healthy choices made in conflict trials does not include this participant. One third of trials presented options using images, one third as their item names from the ratings task, and one third featured one option in words and the other as an image; as this study does not focus on differences in choice by image presentation, data from all three option representation trial types are pooled together to maximize the number of trials used for more precise parameter estimation. Presentation order was randomized across trials and participants, while ensuring that the same item did not appear within five trials.

Participants then completed a second version of the food choices task and personality questionnaires; those measures are outside of the scope of this paper and not reported here. The analyses reported here were not tested or performed on this second task, which was part of a larger series of tests of dietary nudges; this second task was always performed after the one used in these results, and participants were not aware that it would occur. For the results of this second task, see[38].

Phase 4: Incentive Delivery. To ensure incentive compatibility, at the end of the experiment one trial was randomly selected, and the food chosen on that trial was given to the participant. Participants could leave immediately after eating one serving of the food or could wait thirty minutes in the experiment room (1 of the 79 participants chose to wait). This procedure encouraged participants to treat each trial as if it were the one that could count for their food compensation.

Statistical Analysis. All statistical analyses were performed in MATLAB. All t-tests reported are two-sided. All mixed effects regressions used full mixed effects regressions with random slopes and intercepts using MATLAB fitglme. Between-subjects regressions were performed using MATLAB regstats. Pearson correlations were performed with MATLAB corr. Estimation of mtDDM parameters was performed using maximum likelihood estimation in MATLAB. Statistical thresholds were set to $p < .05$. All statistical tests that resulted in a p-value less than $1x10^{-10}$ are reported at that level, given the limits on the precision of our statistical analyses.

mtDDM Model. We simulated choices and response times for a multi-attribute, time-dependent DDM (mtDDM). In this model, a relative value signal (RVS) evolved in 10-ms time steps per convention. At each time step *t*, a weighted amount of the relative (left minus right) taste (T_L–T_R) and health (H_L–H_R) value difference was added the RVS. When the RVS reached the boundary for the right or left item, a choice was considered as being made for that food. The value signal evolved per equation (1). Parameter τ determines the drift latencies, set by t^*_T and t^*_H:

$$RVS_t = RVS_{t-1} + (\tau_T \cdot \delta_T)(T_L - T_R) + (\tau_H \cdot \delta_H)(H_L - H_R) + \varepsilon_t \qquad (1)$$

where,

$\tau_T = 1$ if $t \geq t^*_T$, and $\tau_T = 0$ otherwise;

$\tau_H = 1$ if $t \geq t^*_H$, and $\tau_H = 0$ otherwise.

In this model, ε represents i.i.d. Gaussian noise with a standard deviation fixed to σ = 0.1. The drift latency parameter t* represented the time before which each attribute's relative value does not contribute to the RVS, and after which it contributed at a rate determined by its drift slope. For speed of estimation, this model assumes that the non-decision time proposed in standard DDM models (i.e., the time during the trial not allocated to evidence accumulation) is included in both taste and health drift latencies.

Per-participant DDM Parameter Estimation. We estimated five parameters of the mtDDM (taste and health drift slopes, taste and health drift latencies, and boundary width) for each participant in MATLAB. Using a grid search, the best-fitting parameters for each subject were determined using maximum likelihood estimation. See Supplemental Methods for more details on this procedure.

DDM Simulation. A stimulus set was constructed using seven hypothetical disciplined foods that ranged in health-taste value pairs from (1,0) to (5,4), with higher numbers representing foods that score higher on each attribute dimension. A hypothetical indulgent food was fixed to a health-taste value pair of (0, 5). In this way, the indulgent food was always tastier, but less healthy, than the disciplined food on that hypothetical trial. The following mtDDM parameters for this simulation were fixed: Taste drift slope = Health drift slope = .01; noise σ = .1; symmetrical boundaries = (-1,1); Taste latency = 200 ms. To assess how the relative speed of health information's entrance into the decision process (it's latency) influenced choices and response times, health's latency was varied from 20 ms to 400 ms in 10 ms increments. In this simulation, as in our model estimation (below), the relative value signal evolved in 10 ms time steps. For each trial, 1,000 choices were simulated, and proportion of disciplined choices and mean response times were recorded.

Predicting Choices Disciplined Choices Using Per-Participant mtDDM Parameters. To compare the mtDDM's ability to predict the proportion of healthy choices made by participants to a model with no latency, two simulations were performed and compared to the observed experimental data. First, a simulation was performed that included the latency parameter. To perform this simulation, each participant's best-fitting five mtDDM parameters (taste and health drift slopes, taste and health drift latencies, and boundary width) were first obtained (see Methods section

Per-participant DDM Parameter Estimation). For each Conflict Trial (choices between a tasty, unhealthy option and a healthy, not tasty option) experienced by a participant, 1,000 decision processes were simulated using the participant's mtDDM parameters. A choice for the healthier, less tasty option was said to be made if the majority of simulated processes were in favor of that option. This resulted in a predicted choice, for the healthy or unhealthy option, for each participant and trial in the task. These were then compared to the participant's actual proportion of healthy choices made in the task. This procedure was then repeated for a second DDM, model. This model held the latency of taste and health to be constant, and equal to the earlier of the two latencies in the model. Again, the proportion of disciplined choices was predicted for each participant and compared to the observed number.

Data and code availability: The authors declare that the data and code supporting the findings of this study will be available within the article's Supplementary Information File upon publication.

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