Healthful choices depend 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 that only a single value guides decisions, choices often involve multiple attributes that could make separable contributions to choice. Here, we fit incentive-compatible dietary choices to a multi-attribute, time-dependent drift diffusion model (mtDDM), in which taste and health could differentially influence the evidence accumulation process. We found that these attributes shaped both the relative value signal and the latency of evidence accumulation in a manner consistent with participants' idiosyncratic preferences. Moreover, by using a dietary prime, we showed how a healthy choice intervention alters mtDDM parameters that in turn predict prime-dependent choices. Our results reveal that different decision attributes make separable contributions to the strength and timing of evidence accumulation – providing new insights into the construction of interventions to alter the processes of choice.

Main

Simple choices, like those between food items, have been characterized using sequential integrator models such as the drift (or decision) diffusion model (DDM)[1-4]. In the DDM, choices arise from a process that dynamically integrates 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. These models have been enhanced to account for various features of the decision process, allowing them to better explain choices and to generate new insights into cognitive processes. For example, gaze,[5] and pupil dilation,[6] and neural data[7-11] have incorporated the influence of attention and neural signals, resulting in improved predictions. See Ratcliff[1] for a review of advances in the DDM.

A key advantage of these models is their ability to dissociate the influences of distinct cognitive processes, such as distinguishing bias toward one choice option from reductions in the amount of evidence needed before deciding. Although current variants of these models provide highly accurate descriptions of the psychometrics of value-based choices (i.e., describe both choices and their response times in laboratory experiments), they do not account for important potential contributors to the choice process, including distinct contributions of different attributes to a single choice[12,13].

Here, we present a multi-attribute, time-dependent, drift diffusion model (mtDDM) 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 attributes, which allows estimation of their unique contributions while controlling for other features of the decision process[14,15]. Second, the mtDDM allows each attribute to begin influencing the decision process at a distinct time ("drift latency"). This builds on previous work in which processing of irrelevant features must be inhibited (e.g., Stroop tasks), potentially through shifts in the drift process or two-stage diffusion processes[16-21]. Similarly, previous efforts to understand the temporal order of events in the brain – such as the timing of automatic and voluntary processes – have enhanced our understanding of cognition and behavior[22,23].

A potential strength of the mtDDM is its ability to distinguish among different pathways that could each lead to an unhealthy choice. Most commonly, an individual could place a large weight on taste or a small weight on health. Alternatively, and non-exclusively, relatively delayed processing of health information might preclude its consideration in the decision process – leading to unhealthy choices that run counter to the decision-maker's preferences. There also could be an interaction between decision weights and the timing of processing; e.g., an earlier entry of health information could compensate for a large weighting on the taste attribute. Any of these pathways could result in unhealthy choices, but cannot be differentiated in canonical models.

Dietary choices have several convenient features that make them ideally suited to testing the mtDDM; most importantly, they 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. In our model, such conflicts can be represented as trade-offs in the separate weights placed on taste and health. Moreover, taste and health have meaningfully different properties, resulting in faster processing of taste than health[12]. This may be because taste is a momentary, immediate, and concrete reward whereas the healthfulness of a food presents only future benefits and involves integration of multiple quantities such as caloric and fat content[24]. Although previous studies have estimated the time at which taste and health are processed[12,13], they did not disentangle differences in the weight placed on each attribute from differences in timing parameters. By estimating both attributes simultaneously, we can assess their independent contributions.

The predictions of the mtDDM are illustrated in the two plots of Figure 1. Suppose that taste and health enter the decision process at similar times (Fig. 1a). In this case, health influences the value signal toward the healthy option's boundary early in the decision process, and the healthier option is chosen. In contrast, Figure 1b depicts an identical decision process, except that health's drift latency is much later, resulting in a large "temporal advantage" such that taste has 300ms longer to influence the value signal. In this example, the value signal has nearly reached the boundary for the tastier option when the health attribute's latency has been reached. Health therefore would have a more limited time to influence the value signal before a choice is made in favor of the tastier, less healthy option (the top boundary).

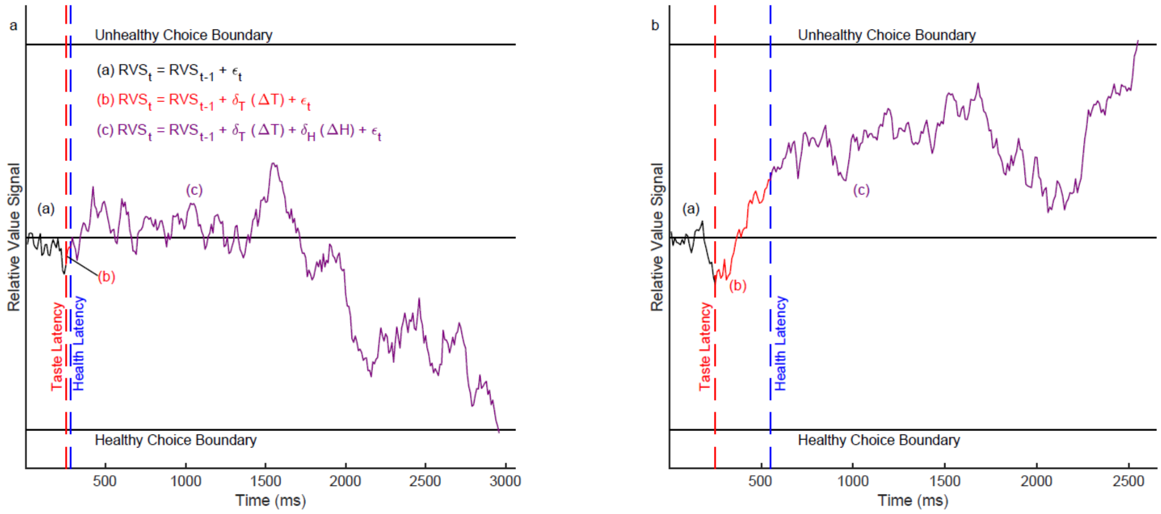


Figure 1. Examples of the decision process modeling within the multi-attribute, time-dependent drift diffusion model (mtDDM). In these example choices between a tasty food (tasty but unhealthy) and a healthy food (healthy but not tasty), a relative value signal (RVS) begins with a value set by a bias parameter (here, zero) and evolves only with noise, ε, at every timepoint t as depicted in equation and segment "a". Once the taste latency is reached (red dashed line), the relative (tasty–healthy) taste value, ΔT, begins contributing to the RVS at a rate determined by its drift slope δ_T ("b"). After the health attribute latency (blue dashed line) is reached ("c"), relative health value, ΔH, 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 reached when the RVS becomes equal to or greater than the boundary for an item. (**a**) In this example, a simulated RVS path is displayed for a choice in which the difference in taste and health attributes are ΔT=1 and ΔH=-7, and mtDDM parameters are set to δ_T=0.005 units/ms, δ_H=0.0009 units/ms, t^*_T=200 ms, t^*_H=300 ms, bias=0, and tasty option boundary=1 and healthy option boundary=-1. Taste and health enter the decision process at similar times, which leads to an early contribution of the health attribute to the RVS, and a healthy choice. (**b**) In this example, all parameters are the same except that the taste attribute has a large "temporal advantage" of 300 ms. That is, due to a later entry of health to the decision process (at t^*_H=500 ms), it begins contributing to the RVS later than in the previous example. Thus, the tasty option boundary is crossed before the health attribute has a significant influence on choice. Figure adapted from[25].

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 (Extended Data Figure 1). Two behavioral primes were also employed to shape participants' dietary goals via attention to either health or taste attributes, respectively. By focusing attention to each attribute in independent participant groups using a between-subjects design, 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[26], an intervention that increases attention to one attribute could increase its rate of accumulation and therefore bias choice – independently of any effects of dietary 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.

Interventions directed at improving choice have found limited success, especially information-based interventions or those targeted at changing patterns of conscious thought[27,28]. Therefore, it is critical to identify the mechanisms underlying what seem to be failures in dietary self-control – particularly if healthy choices might depend on something other than self-control or preferences[29-32]. For example, if healthy choices are facilitated in part by other features of the decision process, such as the time at which health information is processed, harnessing those features may aid in the development of effective interventions. This paper goes beyond introducing an innovation to sequential integrator models to also suggest ways in which the decision process could be nudged to improve choice.

Results

mtDDM Predictions. First, we derived qualitative predictions for how our key new parameters – specifically, the taste and health drift latencies – interact with taste and health drift slopes to influence healthy choices. A series of simulated mtDDMs were performed using an artificial choice set with health and taste values like those in our experimental dataset. Taste's slope and latency were fixed (to 0.08 units/ms and 500 ms, respectively) and health's slope and latency was varied so that the influence of changes in the relative (Taste – Health) latency and slope on choice could be visualized (see Supplemental Information for details).

When taste and health drift slopes are equal (Figure 2, purple line) agents made more healthy choices as health latencies became earlier (left to right). This pattern held when taste slopes were larger than health slopes (red lines). Importantly, differences in taste and health drift slope matter less for later health latencies (Figure 2, far left), and matter much more for earlier health latencies (far right). This indicates that as latencies diverge, the influence of slope changes, implying an interaction between the two parameters. Of note, changes in latency had a bigger effect on the attribute whose parameters were fixed, such that an exactly symmetrical effect would be obtained were health parameters to be fixed instead (Supplementary Figure 1D). See Supplemental Information for more details.

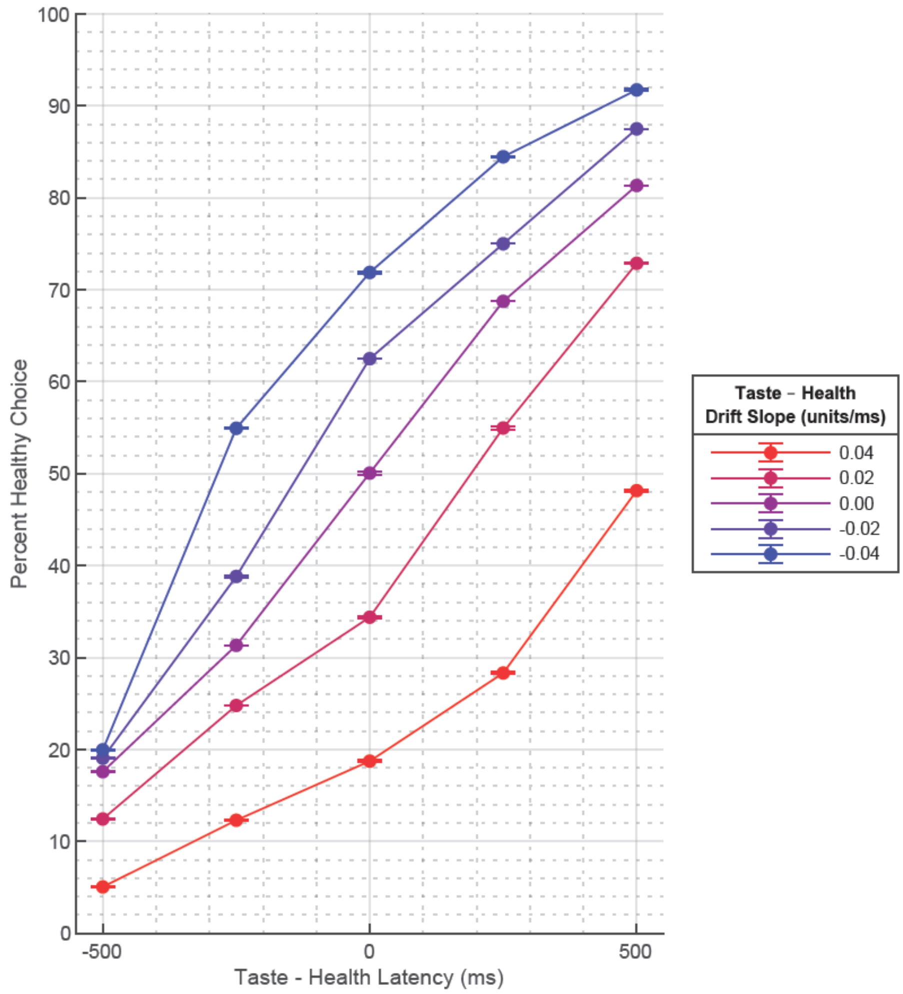


Figure 2. Predicted results of the mtDDM. The proportion of healthy choices (y-axis) predicted by simulations of the mtDDM are plotted for different relative latencies (x-axis). Colored lines show the percent of healthy choices broken out by value difference. Red colors represent simulated agents in which the taste drift slope was larger than health drift slope, and Blue colors represent agents in which the health drift slope was relatively larger.

Behavioral Results. We performed several tests to ensure that participants were choosing according to their preferences in both prime conditions and that their response times (RTs)fit expected patterns. Choices were significantly related to each option's reported wanting for both the health- and taste-primed participants (Fig. 3a; mixed effects slope: health prime mean=1.04, d=1.79, t_{39}=11.34, p<0.001, 95% CI=[0.85 1.22]; taste prime mean=1.32, d=2.37, t_{38}=14.80, p<0.001, 95% CI=[1.14 1.50]). Logistic regression slopes were statistically significantly smaller in health-primed participants (d=-0.51, t_{77}=-2.24, p=0.03, 95% CI=[-0.54 -0.03]).

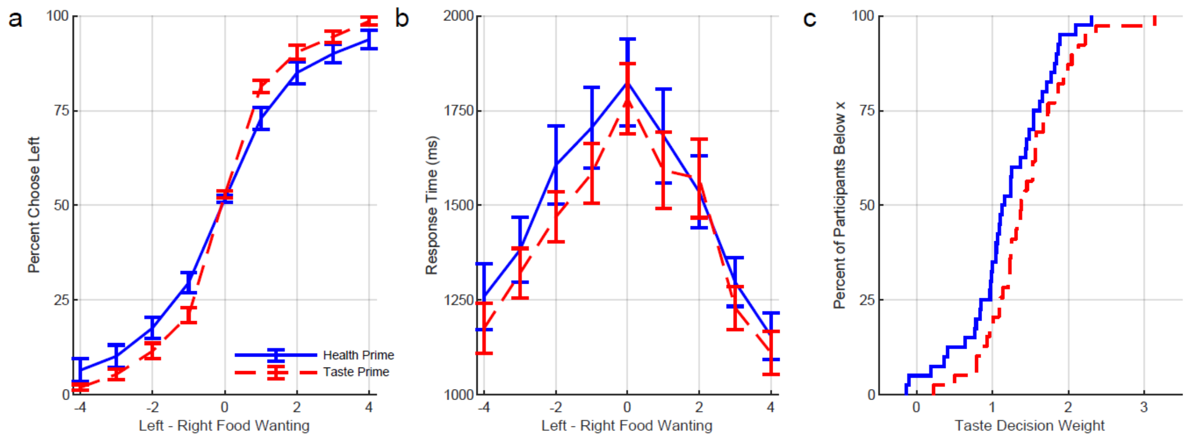


Figure 3. Behavioral results. (**a**) Effects of value difference (Left – Right Food Wanting) on choices. Positive numbers on the x-axis represent cases in which the left item was higher in reported food wanting (N=79; mixed effects slope: health prime mean=1.0, *d*= 1.79, t_{39}= 11.34, *p*<0.001, 95% CI=[0.85 1.22]; taste prime mean=1.32, *d*=2.37, t_{38}=14.80, *p*<0.001, 95% CI=[1.14 1.50]). (**b**) Mean response time (RT) is shown as a function of choice difficulty as measured by the difference between wanting for the right item and for the left item. A difference of zero indicates a difficult choice between two equally-wanted options, and a 4 or -4 indicates an easy choice between items with opposite wanting (N=79; mixed effects quadratic slope: health prime mean=-45.38, *d*=-1.45, t_{39}=-9.15, *p*<0.001, 95% CI=[-54.19 -34.58]; taste prime mean=-41.24, *d*=-1.75, t_{38}=-10.93, *p*<0.001, 95% CI=[-48.88 -33.60]). (**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 (N=40,39; means 1.18 vs. 1.44, *d*=-0.47, t_{77}=-2.09, *p*<0.001, 95% CI=[-0.51 -0.01]). For plots A and B, error bars represent standard error of the mean. For all plots, the health prime condition is represented by the blue solid line and taste prime condition by the red dotted line.

Faster RTs for conflict than non-conflict trials (Supplementary Figure 2a; mean=1558 ms, 1630 ms; paired t-test of log(RTs) d=-0.16, t_{77}=-3.34, p=0.001, 95% CI=[-0.08 -0.02]) were driven by fast unhealthy choices, as healthy choice RTs were markedly longer (Supplementary Figure 2b; mean=1917 ms, 1493 ms; paired t-test of log(RTs) d=0.61, t_{76}=7.33, p<0.001, 95% CI=[0.15 0.27]). This is expected from any DDM with separate weights on taste and health and is the result of the accumulating advantage of taste information during the decision process (see "Response Times by Choice and Trial Type" section of Supplement). RTs increased with choice difficulty – as measured by a difference of zero in reported wanting indicating a difficult choice between two equally-wanted options – for both groups (Fig. 3b; mixed effects quadratic slope: health prime mean=-44.38, *d*=-1.45, t_{39}=-9.15, *p*<0.001, 95% CI=[-54.19 -34.58]; taste prime mean=-41.24, *d*=-1.75, t_{38}=-10.93, *p*<0.001, 95% CI=[-48.88 -33.60]). Quadratic regression slopes were not statistically significantly different between the taste than health prime (*d*=-0.11, t_{77}=-0.51, *p*=0.61, 95% CI=[-15.42 9.13]), nor were average RTs (means 1628 vs. 1554 ms, *d*=-0.03, t_{77}=-0.13, *p*=0.89, 95% CI=[-0.14 0.12]). These results indicate that individuals used value to guide choice in both conditions, and that health-primed participants weighted wanting less than taste-primed participants.

We next estimated the influence of our behavioral prime on choice using each food's taste and health differences, to estimate the weight each participant placed on taste and health information in their decisions, and how this changed depending on the prime they received. We found that health-primed participants placed significantly less weight on taste information (Fig. 3c; means 1.18 vs. 0.44, d=-0.47, t_{77}=-2.09, p=0.04, 95% CI=[-0.51 -0.01]), and there was a statistically marginally significant increase in the proportion of healthy 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, p=0.057, 95% CI=[-0.01 0.83]).

Fitted parameters of the mtDDM. Using participants' choices and RTs, we fit five mtDDM parameters (Table 1; see Supplementary Figure 3 for parameter distributions). 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 evidence required to make a choice ("Boundary", b). Taste drift slopes were larger than health drift slopes (d=1.83, t_{78}=10.91, p<0.001, 95% CI=[0.04 0.05]), reflecting a greater emphasis on taste information in evidence accumulation. Together, these results confirm findings from the previous literature that taste has an overall "weighting advantage" in the choice process. Drift latency was significantly earlier for taste than for health (d=-0.98, t_{78}=-6.22, p<0.001, 95% CI=[-603 -311]). 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 may explain taste's greater influence on the relative value signal and subsequent decisions.

Table 1 | Average best-fitting mtDDM parameters.

Parameter	Mean (SD)	Min	Max
Taste Drift Slope, δ_T (units/ms)	0.062 (0.030)	0.003	0.148
Health Drift Slope, δ_H (units/ms)	0.017 (0.018)	0	0.086
Taste Drift Latency, t^*_T (ms)	409 (245)	10	1920
Health Drift Latency, t^*_H (ms)	866 (611)	20	2750
Boundary, b (units)	1.414 (0.200)	1.088	1.950

Correlation between parameters. There was not a statistically significant correlation between taste and health drift slopes (Pearson ρ=-0.12, p=0.29) nor between taste and health drift latencies (ρ=0.02, p=0.87). Each attribute's drift slope and latency were not statistically significantly correlated (Taste, Pearson ρ=0.11, p=0.32; Health, Pearson ρ=-0.11, p=0.32). Boundary width, typically linked to response caution[33-37](although see[38]) was not statistically significantly related to health drift slopes or taste drift latencies (p>0.12). However, there was a statistically marginally significant correlation between boundary width and taste drift slopes and a statistically significant correlation between boundary width and health drift latencies (δ_T, Pearson ρ=-0.20, p=0.07; t^*_H, Pearson ρ=0.35, p=0.001). This could arise from artifactual interdependencies between model parameters[39-41] resulting in trade-offs between drift rates, latencies, and boundaries. However, we did not find a statistically significant correlation between slope and boundary parameters in in the recovery dataset (Taste Slope, Pearson correlation ρ=-0.09, p=0.36; Health Slope, Pearson ρ=-0.17, p=0.09), but did for latency and boundary (Taste Latency, Pearson correlation ρ=0.37, p<0.001; Health Slope, Pearson ρ=0.25, p=0.01) Alternatively, individuals who process health information later – or who had a smaller contribution of taste information during evidence accumulation – may have required more evidence to make a choice. This 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 Results section. See Supplementary Figure 4 for parameter correlations.

Model validations and comparisons. To validate the model, a parameter recovery was performed (see Supplemental Results and Extended Data Figure 2). This ensured that a large drift slope for one attribute would not lead to inaccurately fast estimate of that attribute's latency. The mtDDM also was tested against and performed better, as assessed by lower Bayesian Information Criterion (BIC), than four alternative models (see Extended Data Figure 3 and Supplemental Results): one in which only slopes, and not latencies varied by attribute (multi-attribute DDM, mDDM); one in which only latencies, and not slopes, varied by attribute (latency DDM, latDDM); one in which attributes vary in the times when they stop rather than start contributing to the value signal (stopping time DDM, stDDM); and one in which taste and health have equal slopes and latencies (simple DDM, sDDM). Lastly, we tested, but do not find evidence for, the possibility that latencies differences could arise from differences in unhealthy and healthy choice non-decision times (see Supplemental Results).

mtDDM vs. single-latency model. We next test the ability of the mtDDM to explain choices and RTs better than a model without separate latencies. This DDM was identical to the mtDDM, but that additionally assumed that taste and health enter the decision process simultaneously. This is functionally equivalent to a simple DDM with one relative value signal (taste + health; see Supplemental Methods)

To compare models, we obtained a BIC using both choices and RTs to classify a correct prediction. Critically, the BIC penalizes the mtDDM for having two latency parameters. The mtDDM performs better (mean BIC values 1111 vs. 1143; d=-2.56, t_{78}=-23.37, p<.001, 95% CI=[-349 -294]), indicating that the addition of attribute-wise latency parameters generates an improvement in model performance, capturing variance in choices and RTs that a single-latency model cannot.

mtDDM parameters proportional to their influences on choice. To validate that the mtDDM accurately reflects participants' choices, we next tested the relationship between drift slopes and the weight placed on each attribute in choice; this relationship is expected because an attribute's drift slope represents the weight placed on that attribute throughout the choice process. These analyses were performed using cross-validated estimation, in which mtDDM parameters were fit using one half of a participant's data, and were used to predict choice in the other half of data (see Supplemental Methods). First, we estimated the relationship between taste and health drift slopes and their decision weights using a linear regression and found that a participant's relative drift slope (taste – health) fitted to one half of trials was correlated with the relative weight (taste – health) during choice in the other half of trials (Fig. 4a; taste – health weights; R^2=0.67, slope=19.57, p<0.001). Furthermore, an increased likelihood of healthy choices in Conflict Trials (when one food was healthier, but less tasty, than the other) was related to relatively smaller taste and larger health drift slopes (Supplementary Figure 5a; R^2=0.67, slope=-5.14, p<0.001). Together, these results confirmed that drift slopes reflected the weight participants placed on taste and health during choice and captured a large proportion of variance in healthy choices, suggesting a correct fitting of the model to choices.

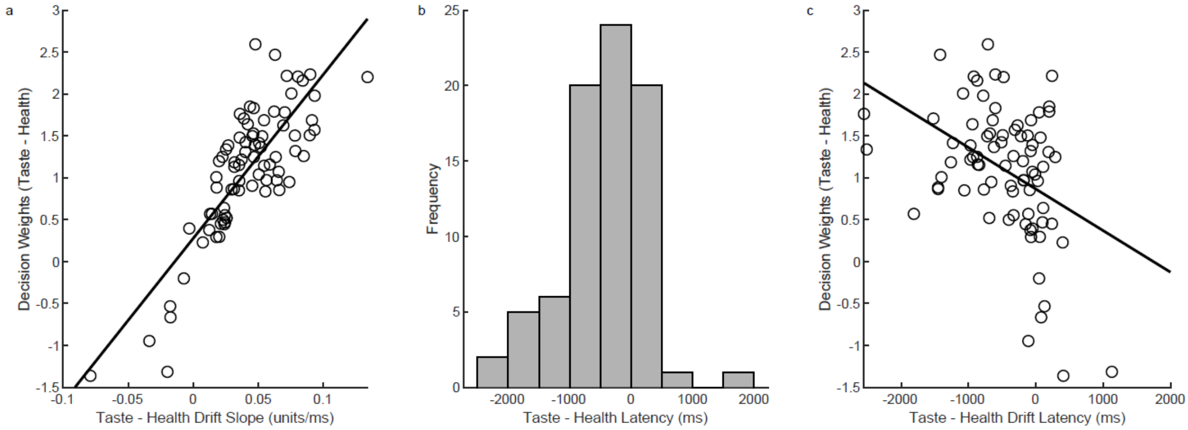


Figure 4. Attribute drift latency parameters related to choice. (**a**) Relative (taste – health) drift slopes shown as a function of their relative logistic decision weights (N=79; R^2=0.67, slope=19.57, p<0.001). (**b**) Histogram depicting relative (taste – health) drift latency across participants (N=79). (**c**) Relative (taste – health) drift latency shown as a function of their relative logistic decision weights (N=79; R^2=0.16, slope=-5x10^{-4}, p<0.001). Lines represent best-fitting linear regression lines.

Because an attribute entering the decision process earlier influences the relative value signal for longer, it should have a greater influence on choice, all else being equal (see Figures 1 and 2). However, latency differences could fail to drive choices if those differences were very small compared to the overall choice period or if the drift slopes were so large that they dominated the choice process. These concerns are partially addressed by the mtDDM's better fit compared to the mDDM, and by noting that the taste information enters the choice process approximately 450 ms earlier than health information (Fig. 4b; one-sample t-test vs. 0, d=-0.70, t_{78}=-6.22, p<0.001, 95% CI=[-603 -311]). This result, combined the mtDDM's lower BICs and the successful parameter recovery, provides converging evidence that drift latencies themselves do differ by attribute, and that taste has a temporal advantage in the decision process.

We next confirmed that, across participants, taste's temporal advantage was related to an increased decision weight on health, relative to taste – again, using cross-validation fitted DDM parameters (Fig. 4c; R^2=0.16, slope=-5x10^{-4}, p<0.001) and thus more healthy choices (Supplementary Figure 5b; $R^{2=}$0.18, slope=1x10^{-4}, p<0.001). A robust regression approach to confirmed that this relationship held even when excluding outliers in Supplementary Figure 5b (slope=6x10^{-5}, p=0.02).

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. They also 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.

Attribute slope and latency independently influence choice. We had hypothesized that drift slope and latency exert independent influences on choice, even when controlling for each other. To test this, we estimated a series of multiple linear regressions using drift slope and latency differences (Taste – Health) to predict individual differences in the proportion of healthy choices made (Table 2). To control for response caution, boundary width was also included. This method tests whether drift slopes and latencies explain different types of variance in the proportion of healthy choices participants made. This analysis was performed using drift slopes fitted using the mDDM, latencies fitted using the latDDM, and boundary width fitted using the sDDM. As expected, drift slopes and latencies predicted individual differences in proportion of healthy choices in the full model. All variables together explained a much larger proportion of the variance in healthy choices than any other model (72%; Model 5 in Table 2); of note, we then performed the same prediction using mDDM drift slopes (i.e., the single-latency model), which explained less variance in healthy choices than a model that included latency differences as well (57%; see Model 1 vs. 5 in Table 2).

Table 2 | Relationship between proportion healthy choices and fitted mtDDM parameters. Weighting advantage was fit using mDDM slopes, Temporal advantage was fit with latDDM latencies, and Bounds were fit with sDDM bounds.

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Weighting Advantage	β=-4.12 [-5.07 -3.36] p<.001			β=-3.24 [-4.04 -2.45] p<0.001	β=-3.84 [-4.71 -2.97] p<0.001
Temporal Advantage		β=2x10^{-4} [1x10^{-4} 2x10^{-4}] p<0.001		β=1x10^{-4} [7x10^{-5} 1x10^{-4}] p<0.001	β=1x10^{-4} [8x10^{-5} 2x10^{-4}] p<0.001
Interaction			β=0.002 [9x10^{-4} 0.003] p<0.001		β=-0.001 [-0.002 -3x10^{-4}] p=0.006
Bounds	β=-0.05 [-0.22 0.11] p=0.52	β=0.55 [0.35 0.75] p<0.001	β=0.30 [0.08 0.52] p=0.008	β=0.20 [0.04 0.37] p=0.02	β=0.15 [-0.01 0.32] p=0.07
Constant	β=0.50 [0.25 0.75] p<0.001	β=-0.37 [-0.63 -0.12] p=0.005	β=-0.10 [-0.39 0.20] p=0.53	β=0.19 [-0.04 0.43] p=0.11	β=0.25 [0.022 0.48] p=0.03
R^2	0.58	0.45	0.20	0.71	0.74
R^2_{adj}	0.57	0.44	0.17	0.70	0.72

95% CI in brackets

Next, we used a stepwise linear regression to test which DDM parameters result in the best-fitting model. All DDM parameters from the above model (taste and health slope and latency differences, the sDDM's temperature parameter and bounds) were added to the regression to predict an individual's proportion of healthy choices. The best-fitting resulting model was one that included slope difference, latency difference, and their interaction (R^2_{adj}=0.71, F(1,74)=64.80, p<0.001). This further indicates that both slope and latency provide independent contributions to explaining healthy choice.

We next performed a bootstrap mediation analysis[42] to estimate the additional contribution of drift latency to the proportion of healthy choices. Health drift latency significantly reduced health drift slope's influence on healthy choice decision weights by 8% (s.e.=.12, p<0.001, 95% CI=[7.66 8.13]). Taste drift slope's prediction of healthy choices was improved, not reduced, by the inclusion of taste latency (-13% s.e.=0.45, p<0.001, 95% CI = [-14.30 -12.52]). Collectively, these results indicate that individual differences in healthy dietary choice was related to both the drift slope and latency parameters of the mtDDM when controlling for the effects of each other, reflecting their independent contributions.

Longer RTs associated with greater influence of health. The above findings suggest that longer RTs could increase the likelihood of a healthy choice, as they would allow slower-processed values like health more time to influence the value signal. To test this, we estimated the relationship between individual trial RT and healthy choice in Conflict Trials. We found that longer RTs were associated with an increased likelihood of selecting the healthier food (Extended Data Figure 4, Model 1; mixed-effects logistic regression R^2_{adj}=0.37, log(RT) slope=0.62 (s.e.=0.05), t_{11698}=11.85, p<0.001), which holds when controlling for the reported wanting of the healthy, relative to tasty, option (Extended Data Figure 4, Model 2; p<0.001). To assess whether this relationship held across participants, we 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=0.49, t_{76}=2.16, p=0.03). This regression was not significant when using non-conflict trial RTs to predict the proportion of healthy choices in Conflict Trials (slope=0.09, t_{76}=0.45, p=0.65). This indicates that longer RTs were correlated with increased likelihood of healthy choices both within and across participants.

Next, we assessed whether this varies by individual mtDDM parameters. If longer RTs promoted healthy choices because they allowed slower-processed health information longer to influence the decision process, then individuals with earlier health latencies would have been less influenced by longer RTs. To investigate this, we first added cross-validation fitted health drift latencies to the previous model predicting healthy choice by RT. RTs remained a significant predictor of healthy choice (Extended Data Figure 4, Model 3; mixed-effects logistic regression, R^2_{adj}=0.48, log(RT) slope=0.39 (s.e.=0.07), t_{5846}=5.21, p<0.001; wanting slope=0.92 (s.e.=0.07), t_{5846}=12.60, p<0.001; t^*_H slope=0.006 (s.e.=0.002), t_{5846}=-2.76, p=0.006). This indicates that after controlling for the weight of health and taste, RTs continued to explain additional variance in healthy choice.

To assess the interplay between latency and RT, we added an interaction term for RTs and health drift latency. If slower health drift latencies require longer RTs to increase the likelihood of a healthy choice, we would see an interaction between health drift latency and RT. We indeed find that the influence of drift latencies on healthy choice depended on a trial's RT; longer RTs were associated with increased likelihood of a healthy choices with late health drift latencies. Further, RT's predictive power was reduced by a third and was no longer statistically significant when drift latency-RT interactions were included in the regression (Extended Data Figure 4, Model 4; mixed-effects logistic regression, R^2_{adj}=0.46, log(RT) slope=0.13 (s.e.=0.12), t_{5845}=1.05, p=0.29; wanting slope=0.92 (s.e.=0.07), t_{5845}=12.52, p<0.001; t^*_H slope=-0.03 (s.e.=0.01), t_{5845}=-3.33, p<0.001; log(RT) x t^*_H slope=0.004 (s.e.=0.001), t_{5845}=-2.77, p=0.006). The inclusion of this interaction term resulted in a statistically significant reduction in the influence of RT on healthy choice, as assessed by 1,000 iterations of bootstrap mediation analysis[42] (mean=30% path strength reduction (s.e.=0.17%) p<0.001 95% CI=[29.84% 29.17%]). These results indicate that longer RTs may promote healthful choices by allowing slower-latency health information to contribute to the value accumulation process.

Dietary primes alter evidence accumulation. Finally, we examined the effects of our two dietary primes – a taste prime and a health prime – on the decision process. There were no statistically significant log(RT) differences between prime groups in Conflict Trials (means=1585 ms,1529 ms, d=0.10, t_{76}=0.43, p=0.67, 95% CI=[-0.11 0.17]), Non-Conflict Trials (means= 1672 ms, 1587 ms, d=0.11, t_{77}=0.48, p=0.63, 95% CI = [-0.10 0.16]), or for healthy or unhealthy choices (healthy choice RT means=1962 ms, 1871 ms, d=0.14, t_{75}=0.60, p=0.55, 95% CI=[-0.13 0.24]; unhealthy choice RT means=1505 ms, 1481 ms; d=0.06, t_{76}=0.27, p=0.79, 95% CI=[-0.11 0.15]). Taste drift slopes were smaller for health- than taste-primed participants (Extended Data Figure 5a; means 0.06 vs. 0.07, d=-0.48, t_{77}=-2.12, p=0.04). Log-transformed taste drift slopes were also relatively smaller than health drift slopes for health primed participants (δ_T-δ_H; Extended Data Figure 5b; means 0.04 vs. 0.05, d=-0.47, t_{77}=-2.08, p=0.04, 95% CI = [-0.03 -7x10^{-4}]). No other parameter differed statistically significantly between condition (Health Slope, mean=0.02, 0.02; d=0.16, t_{77}=0.72, p=0.47, 95% CI = [-0.01 0.01]; Taste Latency, mean=401.75, 416.67; d=-0.06, t_{77}=-0.27, p=0.79, 95% CI = [-125.17 95.33]; Health Latency, mean=791.50, 942.56; d=-0.25, t_{77}=-1.10, p=0.27, 95% CI = [-424.34 122.22]; Boundary Width, mean=1.41, 1.42; d=-0.08, t_{77}=-0.35, p=0.73, 95% CI = [-0.11 0.07]). Together, these results provide no credible evidence that the health prime slowed the overall decision process, per se, but instead that the prime influenced the degree to which taste information influenced the value signal, both in absolute terms and relative to health information.

Discussion

Sequential integrator models such as the DDM have been used to understand the mechanisms underlying binary choices[1,43]. One useful feature of these models is that they allow 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 decision process. We show that both the influence of an attribute on evidence accumulation and the delay before an attribute contributes to the evidence accumulation process differ significantly by attribute – and that between-attribute differences in these two parameters explain a large proportion of the variance in healthy choices. This indicates that models assuming the relative value signal reflects the total stimulus value – and not potentially independent attributions – may be unnecessarily limited in their explanatory power.

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[44]. Our findings support the alternative explanation that tasty dietary choices reflect not only of relative strength of taste preferences but also their relative timing[12,13]. 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 choice. 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.

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[45], such as time pressure[46], which alters parameters of the DDM[47]. Future interventions could either remove time pressure from dietary choices where they often occur, such as at a drive-through window, or 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 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 may provide opportunities for improving choice[29].

Third, we propose that the processes identified for simple multi-attribute dietary choices should exist for other decision domains in which values may be processed differently. For example, in financial choices, one must often make a trade-off between spending money now, and saving for the future[48-50] – 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 saving. Similarly, a multi-attribute DDM has been proposed for social decision making[14], and adding a 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 the mtDDM 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 could alter the drift slope over time. For example, attention has found to significantly influence the evidence accumulation[5]. Second, plausible alternative models exist, such as one with a stopping time for an attribute's consideration. Although we show here that the mtDDM outperforms a stopping time DDM, there may be other choice problems for which it improves model predictions. A time-variable drift rate[51] could address both alternatives by assessing how 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. In addition, the mtDDM presented here assumes that taste and health combine linearly to guide choice. However, non-linear utility functions are often more robust[52]. 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 [48,53,54]. Future work could probe the precise functional form appropriate for evidence accumulation.

Moreover, previous work has found significant trial-to-trial variability in DDM parameters[36,55]. Examination of these fluctuations may help explain within-individual variability in dietary choice. For example, it is possible that when a healthy option is chosen, there is a reconsideration time that does not exist (or is different) for unhealthy choices and that could lead to a shorter health latency. Although we find that health's latency is still longer, on average, in trials in which a healthy choice is not possible, and that latencies could be recovered even with such reconsideration times, examination of the various ways in which health information can enter the decision process would be a fruitful avenue for future research.

Another set of potential limitations are methodological: interdependencies can arise between parameters in multi-parameter models . For example, smaller drift slopes and larger boundary widths could produce similar choice and response time patterns. This is also a concern with the mtDDM, although our successful parameter recovery indicates parameters can be estimated with at least some accuracy. Additionally, the current work presents parameters estimated using only choices and response times. Although this is convenient (both are readily obtained via standard methods for both laboratory and naturalistic experiments) it is also a limitation. This work could be extended by including neural signals, which may provide more accurate estimates or refinements to the model itself. Previous work using neural data to inform multi-attribute choices and models[7,14,56] are a promising direction.

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) 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 healthy choices.

Methods

All procedures and stimuli were approved by the Institutional Review Board at Duke University.

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 [57] 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. Data collection and analysis were not performed blind to the prime condition.

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[58].

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. Data distributions were assumed to be normal, but this was not formally tested. All mixed effects regressions used 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 0.001 are reported at that level, given the limits on the precision of our statistical analyses.

The mtDDM. 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 $\sigma = 0.1$. 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 DDMs (i.e., the time during the trial not allocated to evidence accumulation) is included in both taste and health drift latencies. One parameter commonly used in diffusion modeling is bias at choice outset, often resulting from over-trained motor response as it is introduced before options are identified or processed. As options in this task were randomly and equally presented on the left and right sides of the screen, participants were unable to develop a pre-set motor bias toward the healthier or tastier item on each trial. Further, choices in this mtDDM were fit using left vs. right choices, and not healthy vs. unhealthy choices. Therefore, bias was fixed to zero (i.e., in favor of neither the left nor right option).

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 multi-stage grid search, then optimized using nonlinear minimization. The best-fitting parameters for each subject were determined using maximum likelihood estimation. See Supplemental Information for more details on this procedure.

Parameter Recovery. We performed a parameter recovery exercise of 100 simulated participants to ensure that simulated mtDDM parameters could be recovered using our estimation methods. See Supplemental Information for more details on this procedure and its results, and Figure S7 for correlation between true and recovered parameters.

DDM Simulation to Illustrate Model Predictions. To generate the qualitative predictions for the influence of taste and health latencies on response times and choices displayed in Figure 2, a stimulus set was constructed using health and taste values like those in the experimental dataset's conflict trials – specifically, all possible combinations of value differences ranging from -4 to 4 in which one option had a larger health, and smaller taste, than the other Taste's drift slope and latency were fixed to 0.08 units/ms and 500 ms, respectively. Health drift slopes were varied between from .04 to .16 units/ms in .02 increments had health latencies that ranged from 10 ms to 1000ms, in 250 ms timesteps. Boundary size was fixed to 1 unit. For each of the 25 parameter combinations and 16 taste and health value difference pairs, 1,000 decision processes were simulated, and proportion of healthy choices and mean response times were recorded.

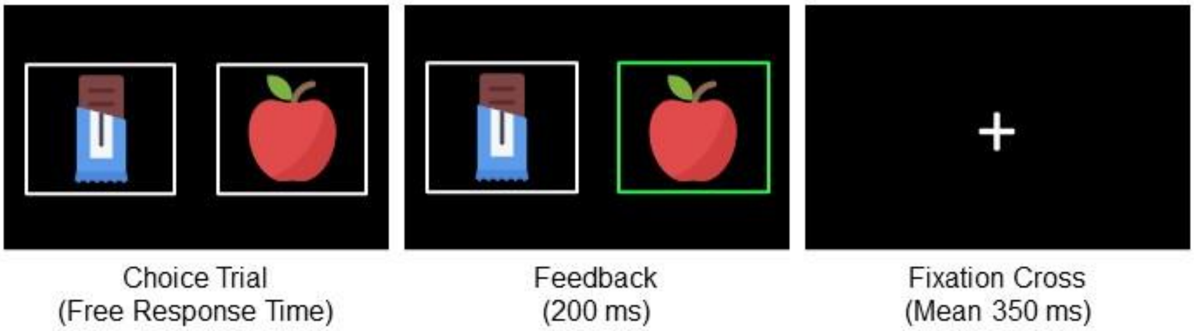
Data availability

Data generated during this study is posted at the Open Science Framework. Link: https://osf.io/trak4/

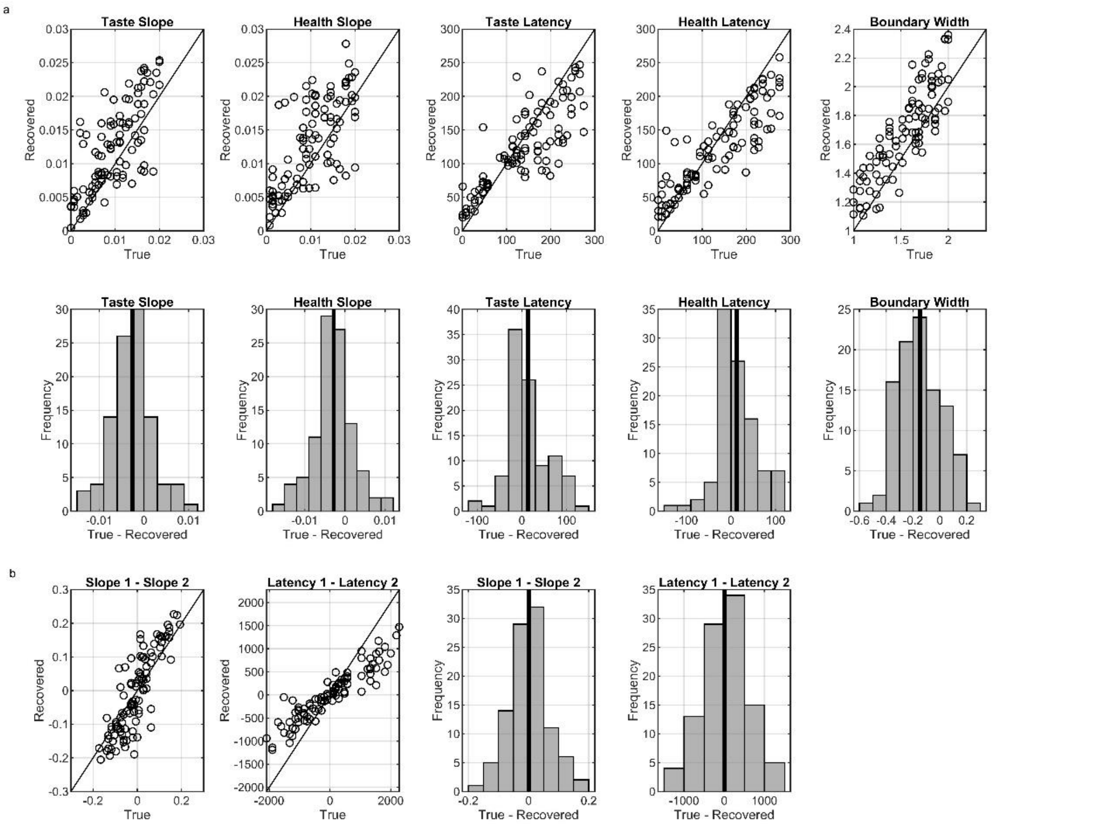
Code availability

Custom code used for stimulus presentation, analysis, and modelling are posted at the Open Science Framework. Link: https://osf.io/d45un/

Extended data



Extended Data Figure 1. Flow of a choice trial. Participants made 300 binary choices with free response time. Foods were displayed on the left and right sides of the screen. After keyboard response, the chosen food was highlighted in green for 200 ms to reflect participant response. Between trials, a fixation cross was displayed in the center of the screen for between 200 and 500 ms (mean 350ms; i.i.d. distributed). Although icons are displayed here, stimuli used were high-resolution real common snack foods photographed on a black background. Icons made by Nikita Golubev & Vectors Market from Flaticon.com.



Extended Data Figure 2. Difference between recovered and true simulated parameters. (a) Each "true" mtDDM parameter is plotted against its recovered estimate. The distribution of differences between true and recovered parameters are shown below each scatterplot. (b) The difference in Drift Slopes and Latencies for Taste and Health are plotted, with the true parameters of the simulations plotted against their recovered parameters. The distribution of differences in true and recovered parameter differences (Taste-Health) are shown below each scatterplot. In each scatter plot, the black line represents a perfect correlation line. In each histogram, the black line represents the mean difference between true and recovered parameter.

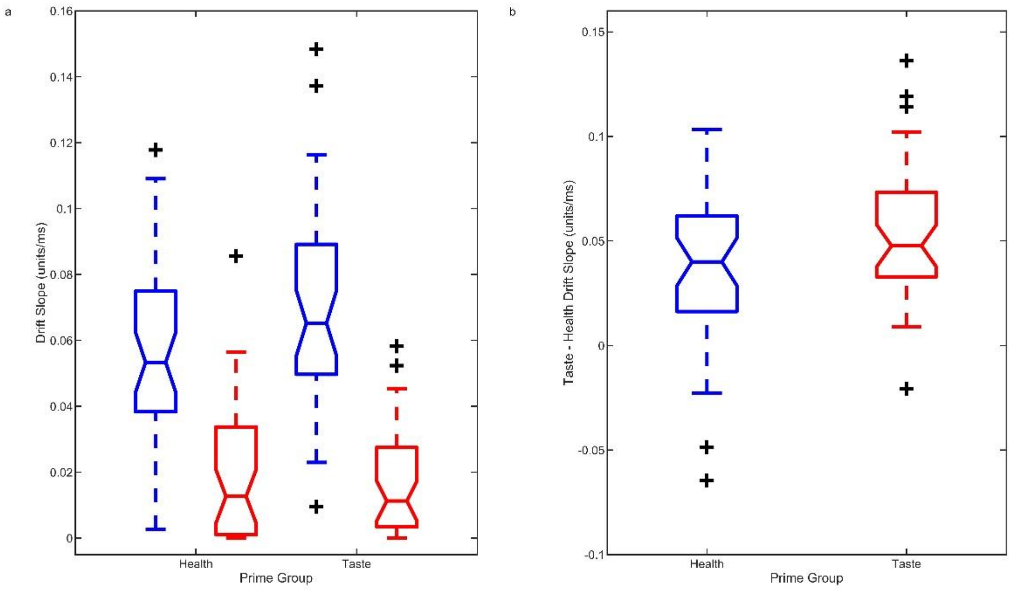
Extended Data Figure 3. Model comparisons.

	Mean BIC	Std. Dev. BIC	Sum BIC	Min. BIC	Max. BIC
mtDDM	1111.21	97.39	87785.52	907.64	1347.02
mDDM	1432.47	148.54	113165.09	1111.26	1764.17
latDDM	1168.99	95.38	92349.93	954.61	1410.01
stDDM	1644.45	115.59	129911.40	1381.28	2005.32
sDDM	1245.58	88.38	98400.87	1081.39	1447.95

Extended Data Figure 4. Association between health's drift latency, response times, and healthy choices

	Model (1)	Model (2)	Model (3)	Model (4)
log(RT)	β=0.62 [0.48 0.76] p<0.001	β= 0.38 [0.23 0.53] p<0.001	β= 0.39 [0.24 0.54] p<0.001	β=0.13 [-0.11 0.36] p=0.29
Reported Wanting (Healthy – Tasty Option)		β= 0.92 [0.78 1.07] p<0.001	β=0.92 [0.78 1.06] p<0.001	β=0.92 [0.77 1.06] p<0.001
Health Latency (t^*_H)			β= -0.006 [-0.01 - 0.002] p=0.006	β=-0.03 [-0.05 -0.01] p<0.001
t^*_H X log(RT)				β=0.004 [0.001 0.006] p=0.006
Constant	β=-5.99 [-7.04 -4.95] p<0.001	β= -3.40 [-4.51 -2.29] p<0.001	β=-2.98 [-4.10 -1.85] p<0.001	β=-1.01 [-2.80 0.79] p=0.27
R^2	0.23	0.47	0.48	0.46
R^2_{adj}	0.23	0.47	0.48	0.46

95% CI in brackets



Extended Data Figure 5. Influence of prime on mtDDM parameters. (a) Drift slopes for food tastiness and healthfulness by prime condition. (b) Difference in taste and health drift slopes by prime condition. For both plots, the center line is the median and box edges represent the 25th and 75th percentiles. The error bars represent the extent of the data

MATLAB's boxplot considered to be not outliers, and black crosses represent outliers. Outliers are determined using MATLAB's default algorithm, in which outliers are data points larger (smaller) than the 75th (25th) percentile plus (minus) 1.5 times the difference between the 75th and 25th percentiles.

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N.J.S. and S.A.H. designed the study. N.J.S. developed the models, collected data, and analyzed data. N.J.S. and S.A.H. wrote the paper.

Competing interests

The authors have no competing interests as defined by Nature Research, or other interests that might be perceived to influence the interpretation of the article.