nature human behaviour

ARTICLES

https://doi.org/10.1038/s41562-020-0893-y

Dissociable mechanisms govern when and how strongly reward attributes affect decisions

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Theories and computational models of decision-making usually focus on how strongly different attributes are weighted in choice, for example, as a function of their importance or salience to the decision-maker. However, when different attributes affect the decision process is a question that has received far less attention. Here, we investigated whether the timing of attribute consideration has a unique influence on decision-making by using a time-varying drift diffusion model and data from four separate experiments. Experimental manipulations of attention and neural activity demonstrated that we can dissociate the processes that determine the relative weighting strength and timing of attribute consideration. Thus, the processes determining either the weighting strengths or the timing of attributes in decision-making can independently adapt to changes in the environment or goals. Quantifying these separate influences of timing and weighting on choice improves our understanding and predictions of individual differences in decision behaviour.

Decisions regularly involve comparisons of several attributes of the choice options. Consider the example of deciding between foods that differ in two attributes: tastiness and healthiness. Often, these attributes are misaligned, creating a conflict between the goal of eating healthily and the desire to experience pleasant tastes. Typically, we assume that choices for the healthier or better tasting food are determined by the values of these attributes together with a subjective decision weight that the decision-maker assigns to healthiness and taste. The assumption that reward attributes are subjectively weighted in the course of decision-making applies not only to food choices but also to many other types of decisions. In fact, it is a core feature of the standard analysis approaches for intertemporal, social and risky decisions[1–4]. Here, we show that this common approach is incomplete because it overlooks the possibility that reward attributes can enter the decision process at different times (in addition to having different weighting strengths). Across several food choice paradigms, we find that there is considerable asynchrony in when tastiness and healthiness attributes are taken into consideration. Furthermore, we demonstrate that the relative weighting strengths (that is, the degree to which an attribute influences the evidence accumulation rate) and the onset times for tastiness and healthiness attributes in the decision process have separable influences on whether people choose to eat healthier foods.

We used an adapted time-varying sequential sampling model that can separate attribute consideration onset times to better understand the dynamic decision processes underlying choices between rewards with multiple attributes. This model allows us to draw inferences on latent aspects of the decision process from the observable choice outcomes and response times (RTs). It is well established that direct measures and estimates of information acquisition, evaluation and comparison processes during choice provide a key means of testing predictions from different models of how stimulus and decision values are constructed or used. Uncovering such features of the decision process enables us to discriminate between and evaluate the plausibility of different models that seek to explain choice behaviour[5]. For example, choice models utilizing not only decision outcomes but also RTs and eye-tracking or computer-mouse-tracking data have provided insights into how and why decision-making is influenced by visual attention, time delays or pressure, additional alternatives, and earlier versus later occurring external evidence[6–13]. Moreover, it has been shown that dynamic accumulation models utilizing RT data provide a deeper understanding of decisions and make better out-of-sample predictions than reduced-form models such as logistic regressions[14,15]. Here, we show that we can also use RT data to determine when specific attributes enter the decision process, in addition to how strongly they influence the evidence accumulation rate. Moreover, incorporating this information into the model improves predictions about individual decision-making behaviour.

An important implication of the finding that different attributes can enter the choice process at separate times is that coefficients from traditional regression models (for example, linear, logit or probit) will represent a combination of both the true underlying weight or importance placed on each attribute and its relative disadvantage or advantage in processing time over the decision period. Therefore, any form of static or synchronous onset dynamic model will fail to fully capture the true underlying choice-generating process. By static we mean models that treat values or value differences as fixed rather than being actively constructed. As a consequence, even though such models may explain multi-attribute choice patterns relatively well if the relationship between attribute weighting and timing is fixed or sufficiently stable, they will fail to explain or predict alterations in decision behaviour if attribute weights and processing onset times can independently change in response to external environmental features or changes in internal cognitive strategies. The plausibility of this latter scenario is underlined by

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mouse-tracking experiments[16,17] showing that different attributes (taste and healthiness) of the same food reward can enter the decision process at separate times. However, the fundamental question of whether the relationship between attribute weighting strength and timing is stable or instead flexible and context-dependent has not yet been addressed.

We addressed this question using an adapted sequential sampling model that quantifies both the weight given to each attribute and its temporal onset during the decision process. This allowed us to explicitly measure whether the weighting strength and timing with which different attributes affect choice are determined by a unitary process (or a set of consistently linked processes) or if, instead, attribute timing and weighting are the results of separable processes. By modelling choices from four separate datasets, which measured decision behaviour under different experimental manipulations (Fig. 1), we show that attribute timing and weighting are determined by dissociable decision mechanisms. For example, we find that explicitly instructing individuals to consider either tastiness or healthiness during the choice process[18] exerts separate effects on attribute weighting strength and timing. In another experiment, we show that transcranial direct current stimulation (tDCS) over the left dorsolateral prefrontal cortex (dlPFC) during food decisions has a selective effect on attribute weighting strength but not timing, thus demonstrating the separability of the underlying neural processes.

Results

We adapted the traditional drift diffusion modelling (DDM) framework[19–21] to allow for each attribute in a multi-attribute decision problem to enter the evidence accumulation process at separate times (Fig. 2a). We chose the DDM as a starting point because this type of sequential sampling model is relatively simple, yet has often been shown to be useful in explaining behaviour across many domains[21] (see Supplementary Discussion). This modified model is a time-varying DDM (tDDM) because the separate consideration onset times for each attribute cause the drift rate to vary over time within a choice. Briefly, we added a free parameter (relative start time (RST)) to estimate how quickly one attribute begins to influence the rate of evidence accumulation relative to another.

The drift rate determining the evidence update at each time step ($dt = 8$ ms) if taste enters first is as follows:

$$E_t = E_{t-1} + \left(\omega_{\text{taste}} \times \text{TD} + \left(t > \left|\frac{\text{RST}}{dt}\right|\right) \times \omega_{\text{health}} \times \text{HD}\right) \times dt + \text{noise} \quad (1)$$

While if healthiness enters first, it is as follows:

$$E_t = E_{t-1} + \left(\left(t > \left|\frac{\text{RST}}{dt}\right|\right) \times \omega_{\text{taste}} \times \text{TD} + \omega_{\text{health}} \times \text{HD}\right) \times dt + \text{noise} \quad (2)$$

Where E is decision evidence, t is the time step, RST is in ms, $dt = 8$ ms, TD is the tastiness difference, HD is the healthiness difference, and ω_{taste} and ω_{health} are subjective weights for taste and health, respectively. Thus, the times at which the weighted value differences in tastiness and healthiness attributes begin to influence the evidence accumulation rate are determined by the RST. When the conditional statement $\left(t > \left|\frac{\text{RST}}{dt}\right|\right)$ is false, it equals 0, while if true it equals 1. Multiplying one of the two weighted attribute values by 0 until $\left(t > \left|\frac{\text{RST}}{dt}\right|\right)$ is true means that this attribute does not factor into the evidence accumulation process for the initial time period determined by |RST|. The RST parameter is defined as the consideration start time for healthiness minus the starting time for tastiness. Note that the standard, synchronous onset DDM is equivalent to the specific case of RST = 0.

We found that the attribute timing asynchrony estimated from RTs by our tDDM was significantly associated with the results from a previously reported mouse response trajectory (MRT) analysis[16]. Participants in that study made choices by moving a computer mouse from the bottom centre to the upper left or right corners of the screen to indicate their choices. Sullivan et al.[16] analysed the response trajectories to determine the relative times at which health and taste attributes enter the decision process. We compared their estimates with those we computed using the tDDM for the same data (Table 1). The time at which healthiness attributes were considered was significantly correlated across the two analysis methods ($r = 0.503$, posterior probability of the correlation being positive ($PP(r > 0)$) = 0.991, 95% highest density interval (HDI) = [0.157, 0.811], Bayes factor (BF) = 7.86), thereby establishing face validity for the tDDM estimates.

In total, we tested the tDDM in 272 participants across four datasets from the following different experimental conditions: MRT choices, standard binary choices in a combined gambling and food choice (GFC) task that was repeated 2 weeks apart, choices following instructed attention cues (IACs) towards taste or healthiness, and choices under tDCS (Fig. 1). The tDDM yielded a better fit to choices and RT distributions than the standard formulation of a DDM with a single, synchronous onset time (overall tDDM Bayesian information criterion = 280,632 versus overall standard DDM Bayesian information criterion = 281,909) (Fig. 3; Supplementary Table 1). Parameter recovery tests demonstrated that choice and RT patterns simulated using known values of the standard DDM and the tDDM could be recovered in each case (Extended Data Fig. 1; Supplementary Fig. 1; Supplementary Results). In other words, our estimation procedures for the tDDM yielded accurate parameter estimates. Critically, the parameter recovery tests also showed that earlier (later) onset of evidence accumulation can be distinguished from stronger (weaker) weighting of evidence (Extended Data Fig. 1e). Furthermore, the tDDM with separate onset times also generated significantly better out-of-sample predictions for food choices than the standard DDM. The mean squared error for this tDDM (0.163) was lower than that of the standard DDM (0.170) (PP of greater accuracy for this tDDM versus a standard DDM = 0.97; see also Supplementary Table 2). Thus, fitting the tDDM results in more accurate predictions about out-of-sample dietary choices.

Adding the separate onset time feature allows the model to capture important choice and RT patterns. Specifically, different onset times for the two attributes can explain the fact that the relative contribution of the tastiness and healthiness attributes to the evidence in favour of one food changes during the decision process. This change in the relative weighting of taste versus healthiness in our data was also seen in simulations (depicted in Fig. 2b–d) and in computing a logistic regression model. This model calculated the influences of taste and healthiness on choices made by participants before or after both attributes were estimated to have begun being considered (Fig. 3; Supplementary Tables 3 and 4). Shared onset time DDMs did not replicate the effect shown in Figs. 2 and 3, Extended Data Fig. 2 and Supplementary Table 5. We note that separate attribute consideration onset timing is a general feature that could be added to many other types of sequential sampling models in addition to the DDM (for examples, see refs. [12,22–28]).

This feature of our tDDM differs in important ways from other types of multiprocess sequential sampling models that include a combination of fast automatic processes and slower deliberate processes (for example, dual process, fast guess, Ulrich diffusion model for conflict tasks)[29–32]. These other frameworks can account for changes in the way evidence is accumulated over time in certain cognitive tasks, but are fundamentally inconsistent with our food choice data. First, responses made before the second attribute is considered are similarly or even more sensitive to the level of the first attribute relative to choices made after both attributes begin to be considered. This indicates that these choices are not random guesses or prepotent or habitual responses. Second, the data from

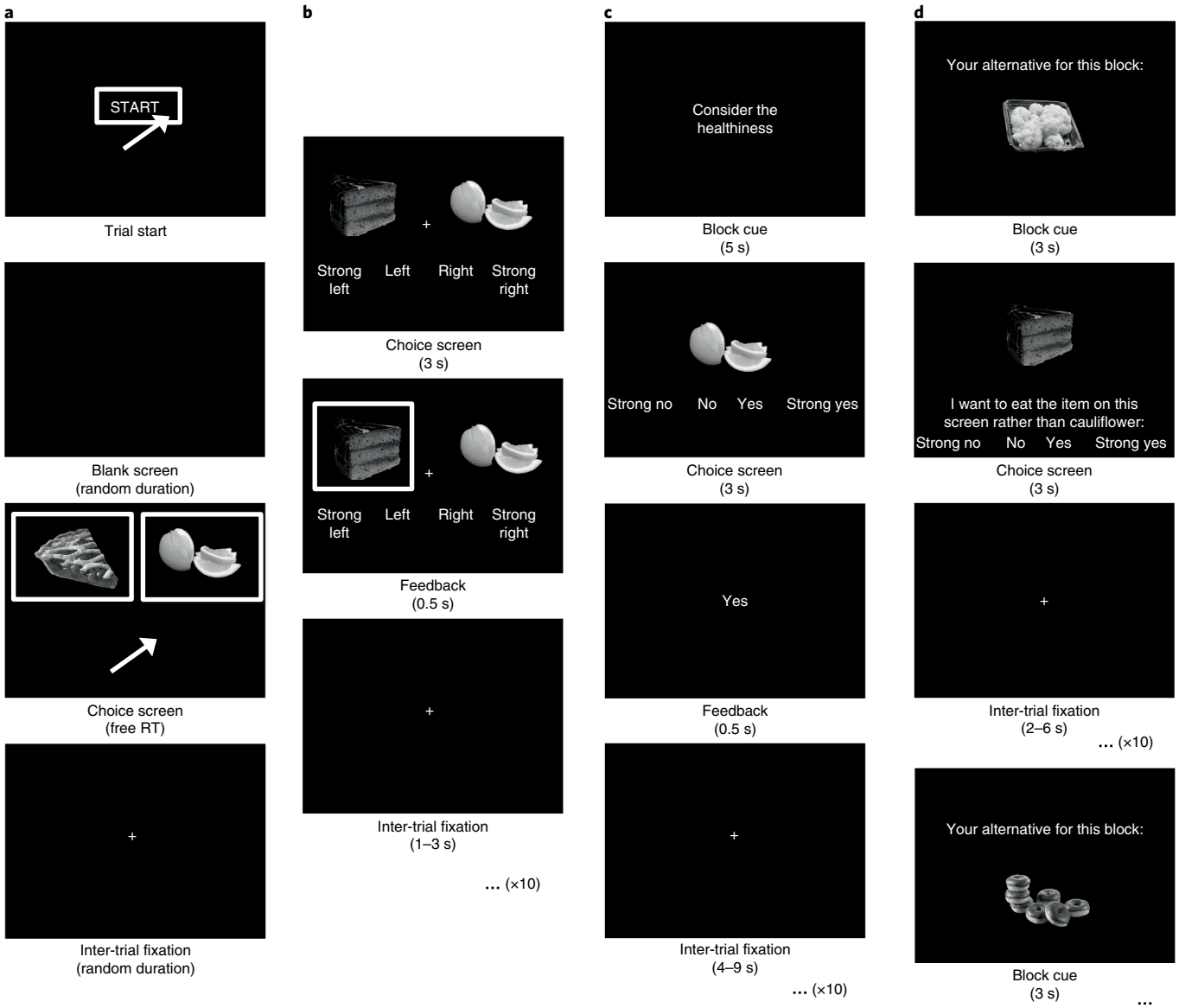

Fig. 1 | Details of the different food choice tasks used in each study. a, For each trial in the MRT task used by Sullivan et al.[16], participants first saw a start screen and had to respond by continuously moving the mouse towards the option they wanted to choose until they reached the box that contained the desired item. **b**, In our GFC study, participants chose between two foods without being instructed to think about healthiness. They had up to 3 s to make their choice on a four-point scale ranging from 'strongly prefer left' to 'strongly prefer right'. Intermixed between the food choices were trials in which participants had to select between decks of cards for monetary rewards. **c**, In the IAC task used by Hare et al.[18], cues to consider a specific attribute or to choose naturally were depicted for 5 s before each choice block of ten trials. Participants then had 3 s to make their choice on a four-point scale from 'strong no' to 'strong yes'. **d**, In our tDCS study, the reference food for the upcoming block was shown for 3 s before each block began. During each block, a series of ten different foods were shown together with a four-point scale from 'strong no' to 'strong yes' (in favour of eating the item shown compared with the reference). The identity of the reference food was written in text below each alternative shown on the screen as depicted.

the IAC experiment described below show that whether tastiness or healthiness is considered first is not automatic. Thus, modifying sequential sampling models to allow different attributes to enter a deliberate consideration process at separate times is more appropriate to explain the outcomes and RTs from the goal-directed choice process studied here.

In the paragraphs above, we established the face validity (that is, correspondence to the mouse trajectory analysis), accuracy (that is, good parameter recovery) and predictive utility (that is, improved out-of-sample predictive accuracy relative to the standard DDM) of our modelling approach. Next, we used a tDDM to test several fundamental questions about how attribute timing and weighting work together, or potentially separately, to influence choice outcomes during healthy choice challenges.

Are more abstract attributes considered later in the choice process?. One may assume that for dietary choices, the RST of the more abstract attribute (healthiness) will lag behind the more concrete and immediately gratifying attribute of taste. However, our results indicated that this is not the case. Pooling the data across all studies, we found that the PP that healthiness is taken into consideration later than tastiness was only 0.48 (mean difference in starting times = 0.001 s, 95% HDI = [−0.05, 0.06, BF (for RST > 0) = 0.21). In total, only 130 out of 272 participants (48%) had RSTs for healthiness

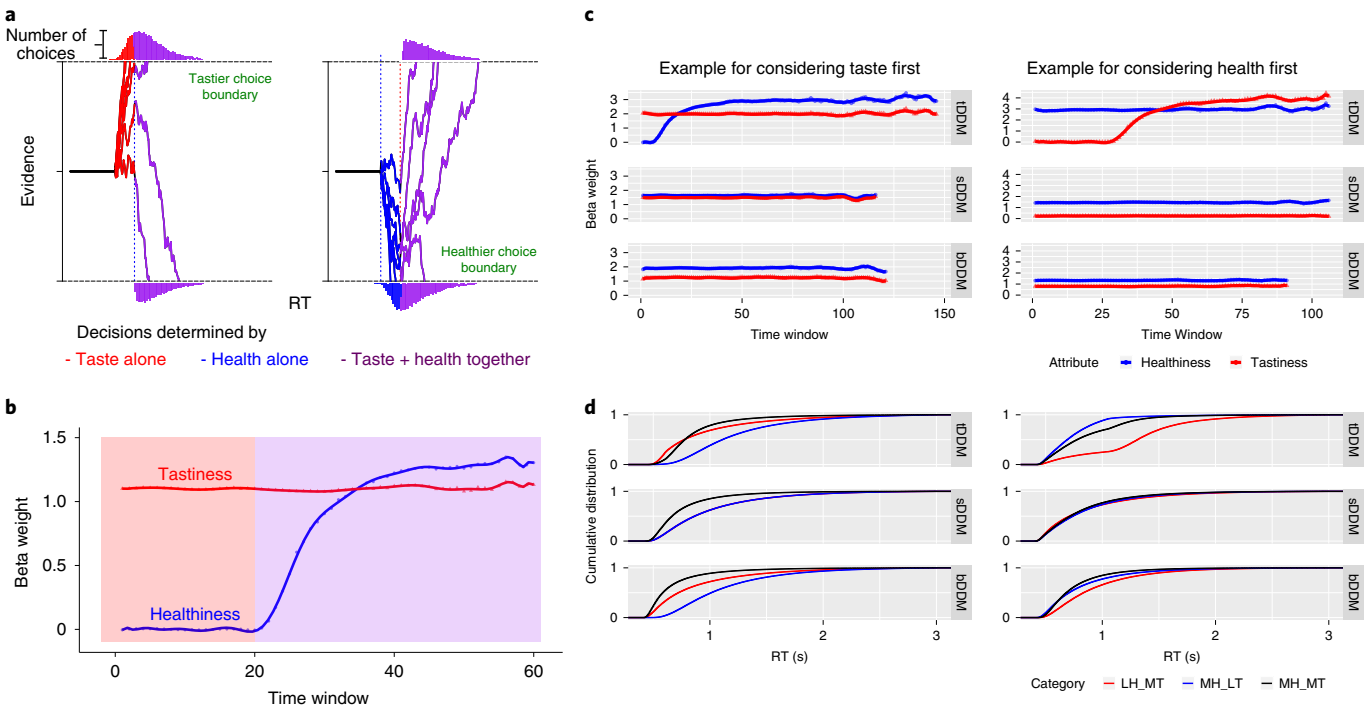

Fig. 2 | Patterns of behaviour predicted by this tDDM. a, The trajectories that begin as red are simulations from an agent that considers tastiness alone first before beginning to consider healthiness attributes. Those that begin as blue are for an agent that considers healthiness before taste. Our tDDM includes an additional parameter (the RST) that represents the average difference in consideration start times between attributes. If a choice boundary is not reached within the RST, then both attributes influence the decision. This is indicated by the lines becoming purple. The histograms at each boundary show the distribution of RTs for each choice outcome. Note that choices in favour of the earlier-considered attribute are, on average, more frequent and faster. **b**, The *y* axis shows the β_1 (red triangles and line) and β_2 (blue circles and line) coefficients from the logistic regression, Choice ~ $\beta_0 + \beta_1 \times$ taste difference $+ \beta_2 \times$ health difference $+ e$, as a function of RT from a simulated agent that considers tastiness first. The *x* axis represents overlapping 100-ms RT windows that slide from minimum to maximum RT in steps of 20 ms. Red shading indicates the period during which only tastiness influences the decision, and purple shading indicates choices made after both attributes are considered. **c**, These plots are analogous to the one in **b**, but are based on simulations from the best-fitting tDDM, standard DDM (sDDM) and tastier starting-point-bias DDM (bDDM) parameters for two example participants. **d**, The plots show the cumulative density functions of the RTs from the simulated choices in **c** as a function of choice outcome. Choice outcome abbreviations: LH_MT, less healthy but more tasty (that is, health challenge failure); MH_LT, more healthy but less tasty (that is, health challenge success); MH_MT, more healthy and more tasty (that is, no challenge).

attributes that were delayed relative to those for tastiness (Extended Data Fig. 3). We used the linear regression model in equation (4) (Methods) to test the relationship between RST and other tDDM parameters. The RST parameter was related to both the tastiness and healthiness weights as well as to the starting point bias parameter (Supplementary Tables 6 and 7), but overall, the linear combination of other tDDM parameters explained only 30% of the variability in RSTs across participants.

Are individual RSTs and attribute weights stable over time?. We tested whether tDDM parameters provide good estimates of stable individual characteristics by comparing parameters estimated from food choices made by the same participants 2 weeks apart. Previous work has shown that the test–retest reliability of choice outcomes in the food choice task is high when participants repeat the same incentivized choices a few days or 1 month apart[33]. In contrast, within each session of our GFC study, participants ($n = 37$) faced 150 trials consisting of a choice between two randomly paired food items. In other words, participants did not complete the exact same set of trials on the two visits, but instead the food pairings randomly varied. This precludes a direct comparison of choice outcomes in the two sessions. Nevertheless, individual characteristics inferred from the tDDM parameter fits were consistent over time. The relative weighting of taste and healthiness attributes (that is, taste > health or vice versa) was the same for 92% of the participants across both visits, while the attribute considered first (that is, RST) was consistent in 76% of the participants. Furthermore, tDDM parameters fit to choices in session one accurately predicted new food choices made in session two 2 weeks later 77% of the time. In comparison, in-sample predictions for session two choices based on tDDM parameters fit to those same choices were correct 78% of the time. These results indicate that taste versus health weighting and consideration onset times may be relatively stable individual characteristics, at least in the absence of experimental manipulations or interventions designed to alter these choice processes.

Effects of attention cues on attribute weights and RSTs. Next, we examined whether directing attention towards either healthiness or tastiness could change the time at which those attributes enter the decision process and whether changes in timing were linked to changes in weighting strength. This analysis was motivated by previous findings[18] that directing attention to the healthiness aspects of a food item resulted in substantial changes in choice patterns (Fig. 4a). In this IAC experiment, instructive cues highlighted health, taste or neither attribute for explicit consideration during the upcoming block of ten food choices. We refer to these three block types as health cued (HC), taste cued (TC) and natural cued (NC). The original analysis of these choice data focused on the regression

Table 1 | Fitted separate attribute onset tDDM parameters by study and condition

Dataset	Parameter estimate					
	ω_{taste}	ω_{health}	Thr	nDT	RST	Bias
MRT						
Keyboard trials	1.42 ± 0.45	0.12 ± 1.03	1.04 ± 0.28	0.65 ± 0.14	0.26 ± 0.36	0.11 ± 0.18
Mouse trials	0.94 ± 0.36	0.27 ± 0.32	1.36 ± 0.25	0.77 ± 0.16	0.14 ± 0.34	0.07 ± 0.19
GFC						
Session one	1.11 ± 0.35	−0.07 ± 0.65	1.29 ± 0.17	0.84 ± 0.13	0.3 ± 0.37	−0.01 ± 0.08
Session two	1.19 ± 0.36	−0.29 ± 0.62	1.19 ± 0.22	0.75 ± 0.12	0.29 ± 0.37	−0.03 ± 0.12
IAC						
NC	1.37 ± 0.79	0.33 ± 1.33	1.27 ± 0.28	0.86 ± 0.12	0.42 ± 0.54	0.00 ± 0 37
HC	0.98 ± 1.12	1.11 ± 0.60	1.39 ± 0.36	0.85 ± 0.14	−0.06 ± 0.55	−0.22 ± 0.33
TC	1.42 ± 0.96	0.47 ± 0.99	1.36 ± 0.36	0.83 ± 0.14	0.28 ± 0.49	0.00 ± 0.31
tDCS						
Sham baseline	0.74 ± 0.67	1.01 ± 0.50	1.29 ± 0.23	0.77 ± 0.16	−0.21 ± 0.40	−0.11 ± 0.26
Sham stimulation	0.67 ± 0.61	1.03 ± 0.55	1.21 ± 0.21	0.71 ± 0.14	−0.10 ± 0.34	−0.14 ± 0.24
Cathodal baseline	0.63 ± 0.81	1.01 ± 0.62	1.26 ± 0.24	0.75 ± 0.14	−0.05 ± 0.44	−0.07 ± 0.24
Cathodal stimulation	0.92 ± 0.45	1.07 ± 0.73	1.19 ± 0.21	0.69 ± 0.11	−0.03 ± 0.38	−0.03 ± 0.22
Anodal baseline	0.60 ± 0.84	1.15 ± 0.48	1.25 ± 0.2	0.75 ± 0.13	−0.09 ± 0.41	−0.08 ± 0.24
Anodal stimulation	0.85 ± 0.6	1.19 ± 0.62	1.16 ± 0.2	0.70 ± 0.12	−0.09 ± 0.38	−0.04 ± 0.25

All parameters are reported as the mean ± s.d. See Methods for details of the parameters. ω_{taste}, weighting factor determining how much the difference in taste attributes contributes to the evidence accumulation rate; ω_{health}, weighting factor determining how much the difference in health attributes contributes to the evidence accumulation rate; Thr, evidence threshold for responding; nDT, non-decision time, which corresponds to the starting time for taste in our model; RST, relative start time for health (timing relative to start of taste processing, where positive values denote that health enters the process later than taste); Bias, starting point bias for the evidence accumulation process (zero = no bias).

weights for taste and health attributes in each choice condition, but did not consider that the cues might change the relative times at which these attributes entered the choice process. Our goal was to determine how potential alterations in attribute timing and weighting contributed to the observed changes in choice behaviour during HC relative to NC blocks.

First, we found that attention cues changed both the relative weighting and timing of taste and healthiness attributes. Compared to the natural choice blocks, 70% of the participants reversed their relative weighting of taste and healthiness in taste or health cue blocks (that is, went from taste > healthiness to taste < healthiness weight or vice versa), and 64% switched whether they considered tastiness or healthiness first. There was not a significant difference in how often participants reversed the order of relative weights (switching from $\omega_{taste} > \omega_{health}$ to $\omega_{taste} < \omega_{health}$, or vice versa) compared with how often they reversed the order of relative onset times (switching from taste first to healthiness first, or vice versa) when moving from attribute cued and natural choice blocks (PP(weight reversal more prevalent than timing reversal) = 0.70, BF = 1.4).

Focusing our analyses on the HC blocks that showed a significant change in choice outcomes compared to natural blocks (Fig. 4a), we found that on average, cueing attention to health attributes both significantly increased the magnitude of the weights for healthiness of the participants and sped up the time at which health entered the evidence accumulation process (relative to taste, that is, RSTs) (Fig. 4b,c; Table 2). These results demonstrate that both the timing and weighting of taste and healthiness attributes can be flexibly and rapidly changed in response to the attention cues preceding every block of ten choices.

Dissociating attribute weighting strengths and timing at the neural level. We next addressed the question of whether attribute weighting strength and timing are implemented by dissociable neural processes. We did so by analysing data from an experiment applying cathodal, anodal or sham tDCS over the left dlPFC during food choices (see Methods for details). Numerous neuroimaging and electrophysiological studies have reported correlational evidence for a role of the dlPFC in multi-attribute choice[34–37]. There is also ample evidence showing that applying brain stimulation (both transcranial direct current and magnetic) over multiple different subregions of the left or right dlPFC is associated with changes in several different forms of multi-attribute decision-making[38–44]. Here, we applied tDCS over a region of the left dlPFC that is correlated with individual differences in health challenge success rates, and in multi-attribute decisions more generally[18,45–55], to uncover the mechanistic changes in the choice process caused by tDCS over this particular region. Stimulation over this region of left dlPFC did not significantly change measures of working memory, response inhibition or monetary temporal discounting in our participants (see Supplementary Results).

Previous studies have suggested that the effects of stimulation over the left dlPFC are strongest during trials in which the participant does not strongly favour one outcome over the other (that is, stimulation effects are greatest in difficult choices) and depend on baseline preferences over the rewards[39,43]. Therefore, we restricted our analysis of health challenge success to trials in which the predicted probability of choosing the healthier food was between 0.2 and 0.8 and focused on the difference in behaviour between baseline and active-stimulation choice sessions. Specifically, we computed a Bayesian hierarchical logistic regression model that accounted for both stimulation type and the healthiness and tastiness differences for each trial in the tDCS dataset (see equation (5) in the Methods for details). We compared the interaction effects by measuring changes in health challenge success for each participant from the pre-stimulation baseline to the active stimulation condition for cathodal and anodal versus sham simulation groups. This revealed a greater decrease in health challenge success under cathodal relative to sham stimulation (Supplementary Table 8; regression

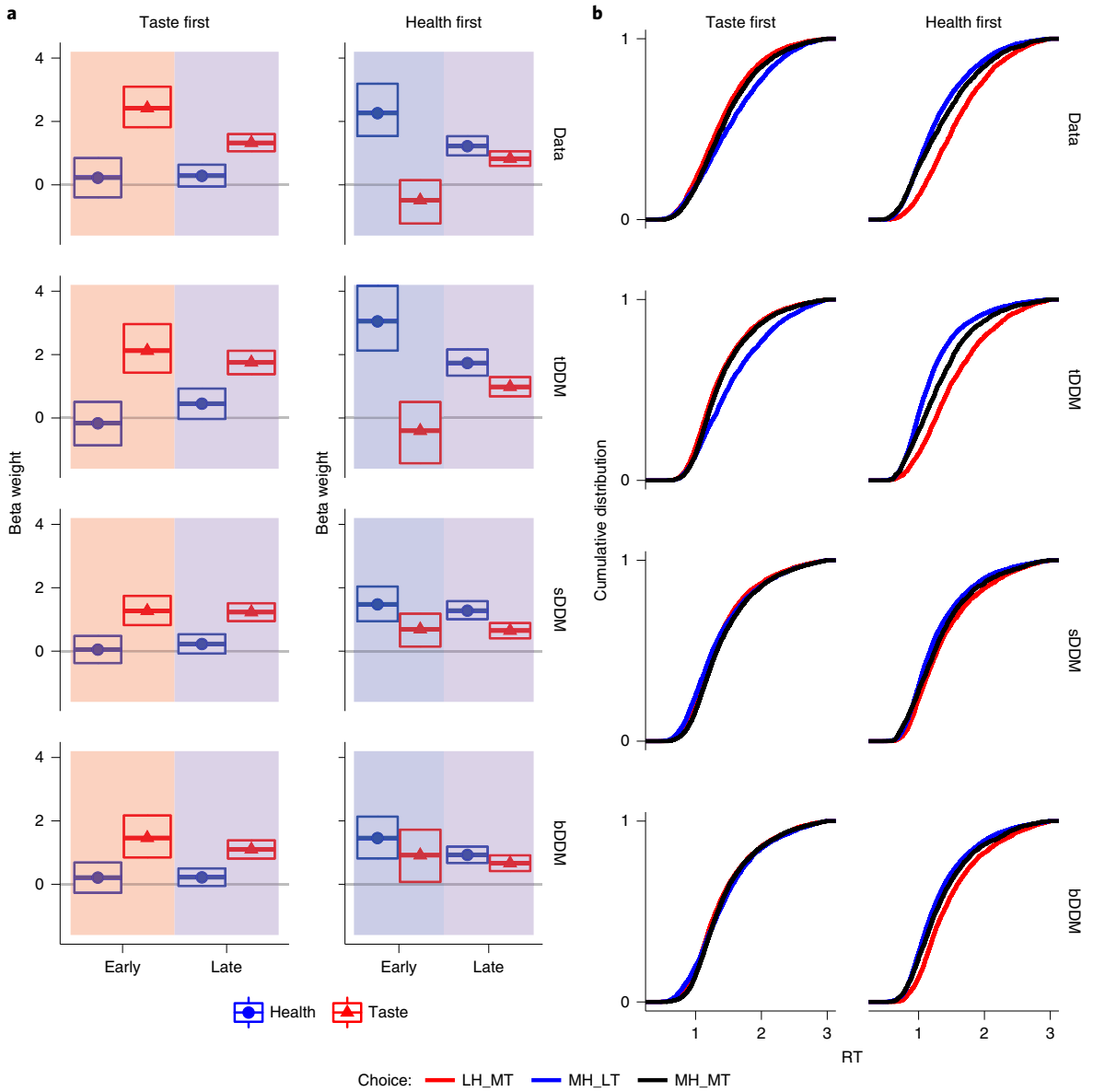

Fig. 3 | Influence of taste and healthiness attributes on choice outcomes and RTs. Top row shows results from the empirical data and bottom three rows show results from data simulated using the best-fitting tDDM, sDDM and bDDM parameters. The tDDM reproduces the time-dependent attribute influence and RT patterns found in the data better than any of the alternative models. **a**, These plots show the mean (filled shapes) and 95% HDIs (open rectangles) of beta weights from the logistic regressions in Supplementary Table 5 and represent the estimated influences of tastiness (red triangle) and healthiness (blue circle) attributes on choice outcomes. These influences are shown separately for early (<1s) and later (>1s) RTs and participants that are estimated to consider taste or health first. The blue, orange, and purple background shading corresponds to Fig. 2 and indicates periods where, on average, health alone, taste alone, or both taste and health are expected to have a significant influence on choices. **b**, These plots show the cumulative distributions of RTs observed in the empirical and simulated data. The left and right columns show data from participants who are estimated to consider taste first or healthiness first, respectively. The three choice outcomes are (red) less healthy but more tasty (LH_MT), (blue) more healthy but less tasty (MH_LT) or (black) both more healthy and more tasty (MH_MT). Choices in favour of the option rated as less healthy and less tasty were rarely made (less than 5% of trials) and are omitted for clarity.

coefficient = −0.32 ± 0.15, 95% HDI = [−0.58, −0.08], PP(cathodal polarity × active stimulation interaction coefficient < 0) = 0.98), but no change in health challenge success for anodal relative to sham stimulation (regression coefficient = −0.03 ± 0.15, 95% HDI = [−0.28, 0.22], PP(anodal polarity × active stimulation interaction coefficient > 0) = 0.4). There was also a main effect within the cathodal stimulation group, which indicates that these individuals had fewer health challenge successes when making food choices under active stimulation compared with their pre-stimulation baseline choices (regression coefficient = −0.31 ± 0.15, 95% HDI = [−0.55, −0.08], PP(active stimulation < 0) = 0.9999). Thus, we find that inhibitory stimulation over the left dlPFC leads to fewer health challenge successes (see also Fig. 5a).

To elucidate the changes in choice processes caused by the stimulation, we fit the separate attribute consideration onset tDDM to dietary choices made during the pre-stimulation baseline and active or sham tDCS sessions. When testing how the tDDM parameters changed between baseline and active stimulation sessions in each

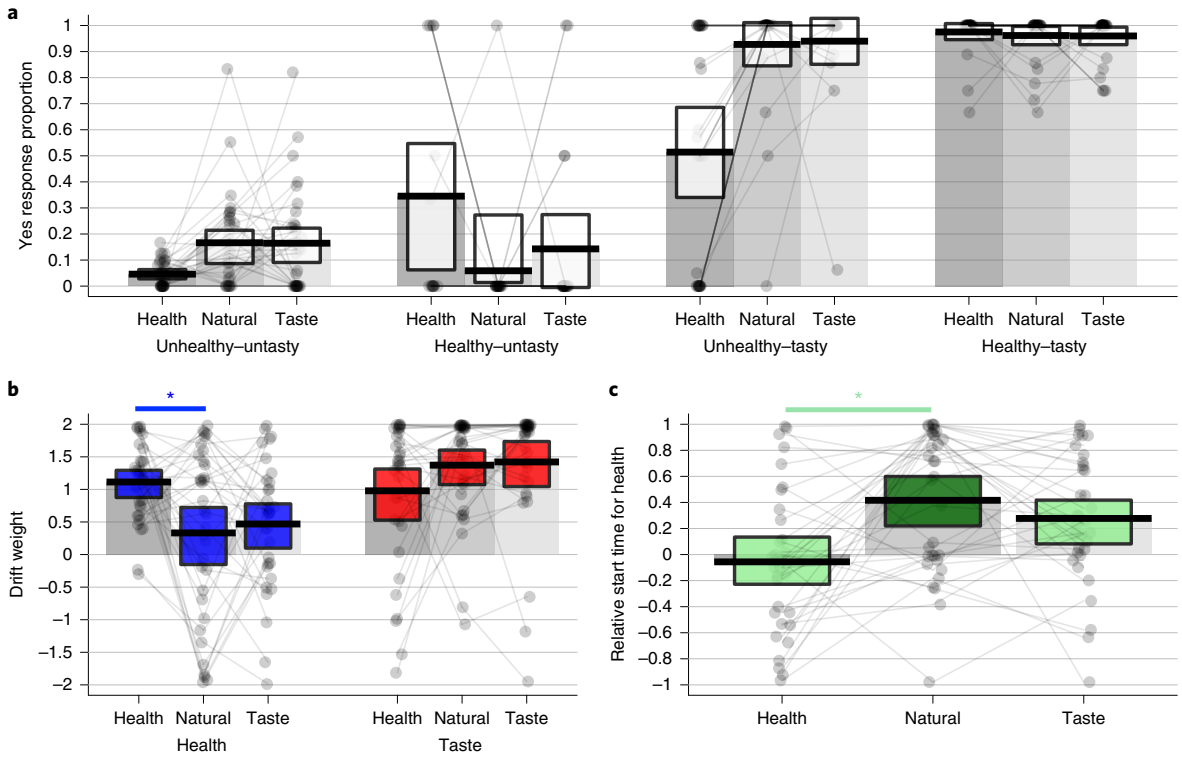

Fig. 4 | Choice patterns and separate attribute consideration onset tDDM parameter estimates for the IAC study by condition. a, The proportion of times that participants ($n = 33$) chose to eat the food (that is, they responded 'yes' or 'strong yes') as a function of attention cue type (health, natural or taste) and taste–health combination of food under consideration (tasty or untasty crossed with healthy or unhealthy). In terms of mean choice proportions, directing attention towards healthiness decreased the proportion of choosing healthy–untasty items and decreased the proportion of choosing unhealthy–tasty items compared with the natural condition. The changes in choices during health blocks were accompanied by higher weights and faster RSTs for healthiness. **b**, Compared to the natural condition, attention cues to health resulted in a higher relative drift weight (arbitrary units) for the corresponding health attribute compared with the natural condition (blue shading). There was no significant change in the relative drift weights of the two attributes during the taste cue blocks (red shading). **c**, Attention cues to health also led to a faster RST (seconds) for health attributes compared with natural blocks (green shading). Once again, there was no significant difference in relative timing between natural and taste blocks. For all plots, the dots within each column represent the value for a single participant in the sample. Darker shading indicates that multiple participants share the same value for that parameter. Black horizontal bars indicate condition means, and white, blue, red or green shaded rectangles indicate the 95% HDIs for each measure. The grey shaded bars in each plot serve to visually separate the columns for each condition and highlight the zero points on the *y* axes. Asterisks in **b** and **c** denote a significant change of the parameter estimate between the health and natural cue conditions.

Table 2 | Changes in separate attribute consideration onset tDDM parameters between attention-cued conditions

	Mean difference	95% HDI	PP	BF
ω_{taste}				
Natural – health	0.354	[−0.113, 0.832]	0.933	1.251
Taste – health	0.455	[−0.088, 1.003]	0.951	1.122
ω_{health}				
Health – natural	**0.746**	**[0.188, 1.325]**	**0.995**	**12.818**
Health – taste	**0.633**	**[0.245, 1.028]**	**0.999**	**39.041**
RST of health				
Natural – health	**0.469**	**[0.2, 0.748]**	**0.999**	**60.868**
Taste – health	**0.336**	**[0.121, 0.548]**	**0.999**	**26.655**

This table shows the effects of attention cues on the tDDM parameters estimated from choice data in the IAC study. Changes in RSTs or weighting parameters (ω_{taste}, ω_{health}) induced by the experimental conditions that are shown in bold were significantly different from zero. Mean differences and their 95% HDIs were computed based on 100,000 samples drawn from the posterior distributions of each parameter[75]. The third column displays the posterior probabilities that differences are greater than zero. All comparisons were made so that a priori predicted effects would be positive.

group, we found that the cathodal group had increased weighting of taste attributes under stimulation compared with baseline choices (mean difference = 0.14, HDI = [0.03, 0.25], PP(cathodal active > cathodal baseline) = 0.99, BF = 5.75; Fig. 5a) and that the change from baseline was greater under cathodal stimulation than sham (mean difference = 0.21, 95% HDI = [0.01, 0.42], PP(Δcathodal > Δsham) = 0.98, BF = 4.20). Crucially, the RST parameters were unaffected during left-dlPFC-targeted cathodal tDCS (Table 3; Fig. 5b). Moreover, the tDCS-induced changes in taste relative to health weighting parameters and RSTs were not significantly correlated ($r = -0.07$, 95% HDI = [−0.325, 0.188], PP($r > 0$) = 0.30, BF = 0.210). Consistent with the lack of significant change in choice behaviour under anodal tDCS, we found no significant changes in any tDDM parameter under anodal stimulation (Table 3). In summary, we found that cathodal tDCS over the left dlPFC changed the relative decision weight placed on taste attributes, but not the speed with which taste, relative to healthiness, began to influence the choice process (Table 3).

Discussion

We have shown that separable mechanisms determine the degree to which an attribute affects the evidence accumulation rate (weighting strength) and the relative speed with which it begins to do so

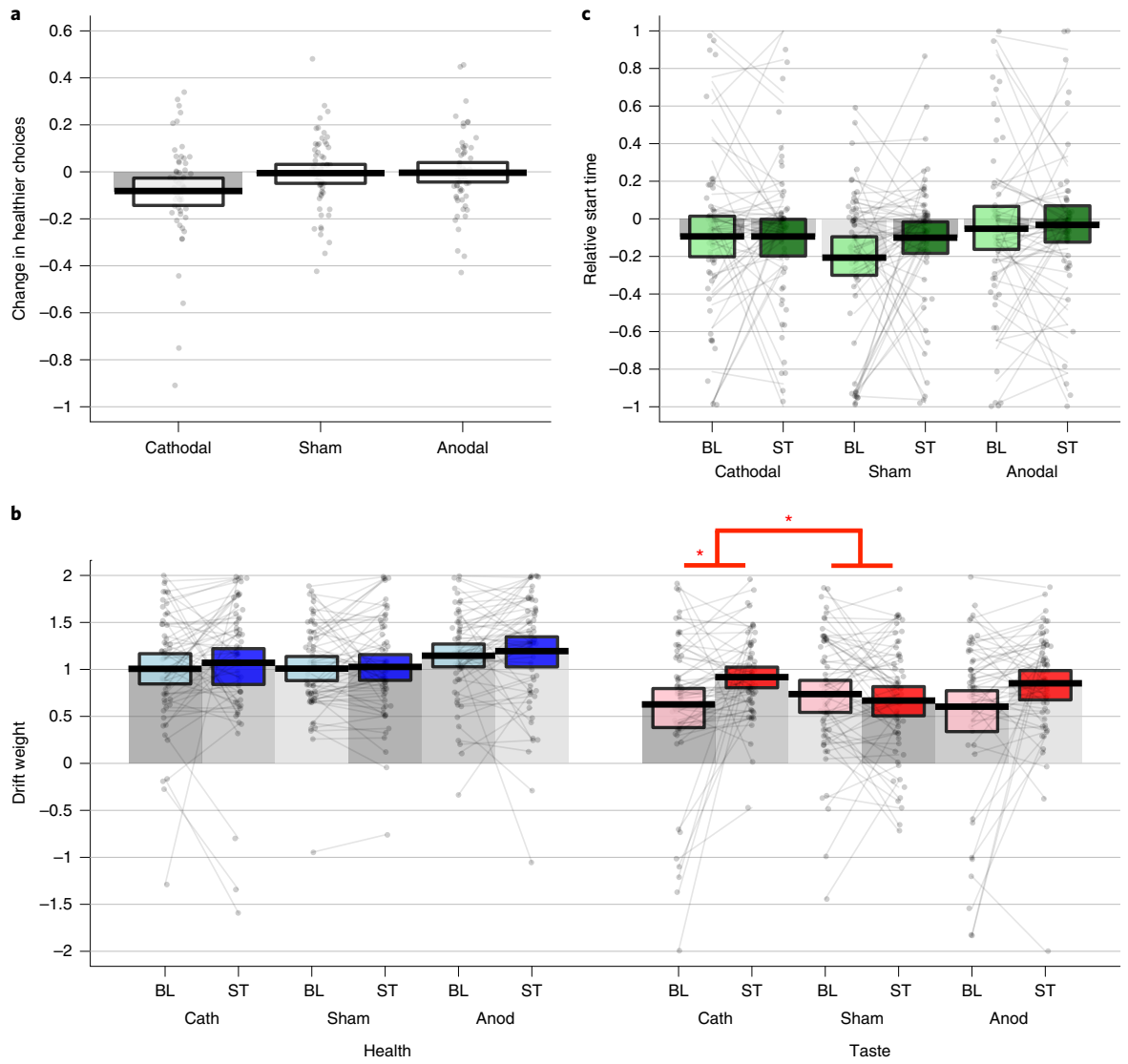

Fig. 5 | Changes in health challenge success and tDDM parameter estimates following tDCS over the left dlPFC. a, This plot shows the raw changes in health challenge success under stimulation compared with baseline across stimulation groups ($n = 58$ anodal, $n = 57$ cathodal, $n = 59$ sham). Unlike the regression summarized in Supplementary Table 8, the effects shown in this plot do not account for the taste or health differences in each choice. Each dot represents the difference between active stimulation or sham and baseline in one participant. Left dlPFC-targeted cathodal stimulation significantly decreased health challenge success (mean decrease = 5.7 ± 0.02%, 95% HDI = [−10%, −1.5%], PP(active cathodal stimulation < 0) = 0.995, BF = 6.41). Note that we tested the change under cathodal stimulation using a method[75] that is robust against outliers such as the two extreme participants near −1. There were no significant differences in healthy choices under anodal or sham stimulation. **b**, Cathodal (cath) stimulation (ST) increased the weighting of taste attributes (ω_{taste}, red shading on the right) relative to baseline (BL) choices; PP(cathodal ST > cathodal BL) = 0.99, BF = 5.75). This change from baseline was greater under cathodal stimulation than sham; PP((cathodal ST − cathodal BL) > (sham ST − sham BL) = 0.98, BF = 4.20). The red horizontal lines and asterisks highlight this main effect and interaction. Anodal (anod) stimulation did not lead to significant changes in attribute weighting parameters, and neither tDCS protocol affected drifts weights for healthiness (ω_{health}, blue shading on the left). The weighting strength parameters are plotted in arbitrary units. **c**, tDCS had no significant effect on the RST parameters (plotted in seconds, green shading). Black horizontal bars indicate group means and rectangles indicate the 95% HDIs for each effect. The grey shaded bars in each plot serve to visually separate the columns for each condition and highlight the zero points on the *y* axes.

(timing). Measuring each of these distinct processes helps to explain individual differences in dietary choices at baseline as well as how behavioural and neurophysiological manipulations effect changes in the decision process. Thus, both attribute timing and weighting strength must be examined if we seek to better understand decision-making at the mechanistic level.

The clearest evidence that timing and weighting strength are dissociable comes from our tDCS experiment, which showed that stimulation over the left dlPFC caused a change in the weights placed on the taste factor, but not the timing of taste versus healthiness attributes during dietary choices. Moreover, changes in the relative weighting and the relative timing of each attribute between baseline and cathodal stimulation sessions were not significantly correlated, which further indicates that the neural mechanisms altered by our tDCS protocol were specifically related to attribute weighting (additional implications of these results are included in the Supplementary Discussion).

In our current work, for example, we found that the relative importance given to a specific attribute, as well as its speed in entering the choice process, could be altered by instructions that directed

Table 3 | Effects of tDCS over the left dlPFC on tDDM parameters

	Mean difference	95% HDI	PP	BF
ω_{taste}				
Baseline – Anodal tDCS	−0.094	[−0.23, 0.043]	0.081	0.047
Cathodal tDCS – Baseline	**0.138**	**[0.027, 0.248]**	**0.993**	**5.748**
Baseline – Sham tDCS	0.072	[−0.087, 0.23]	0.815	0.33
ΔSham – ΔAnodal	−0.185	[−0.41, 0.047]	0.053	0.091
ΔCathodal – ΔSham	**0.215**	**[0.014, 0.42]**	**0.982**	**8.333**
ω_{health}				
Anodal tDCS – Baseline	0.098	[−0.023, 0.221]	0.941	0.267
Baseline – Cathodal tDCS	−0.074	[−0.246, 0.102]	0.197	0.094
Sham tDCS – Baseline	0.025	[−0.082, 0.13]	0.685	0.188
ΔAnodal – ΔSham	0.063	[−0.093, 0.223]	0.787	0.261
ΔSham – ΔCathodal	−0.039	[−0.241, 0.164]	0.349	0.149
RST				
Baseline – Anodal tDCS	−0.002	[−0.098, 0.093]	0.484	0.144
Cathodal tDCS – Baseline	0.021	[−0.095, 0.135]	0.648	0.193
Baseline – Sham tDCS	−0.103	[−0.225, 0.018]	0.047	0.056
ΔSham – ΔAnodal	0.098	[−0.057, 0.251]	0.895	0.764
ΔCathodal – ΔSham	−0.081	[−0.25, 0.086]	0.171	0.106

This table reports changes in the separate attribute consideration onset tDDM RSTs or weighting parameters (ω_{taste}, ω_{health}) as a result of tDCS over the left dlPFC. Rows in bold indicate changes that are significantly different from zero. The Δ symbol always indicates a difference score equal to the value in the stimulation minus the baseline session within a given condition. Rows containing this symbol report differences of differences across conditions. Mean differences (or differences of differences) and their 95% HDI were computed based on 100,000 samples drawn from the posterior distributions of each parameter. The third column displays the PPs that differences are greater than zero. All comparisons were made so that a priori predicted effects would be positive.

attention to that attribute. Although a large body of work has established that value construction and comparison processes are malleable and subject to attention, perceptual constraints and other contextual factors[9–11,56,57], the influence of attribute consideration timing within a given decision is rarely discussed or directly tested. Query theory[58,59] is a notable exception in that it explicitly posits that the order in which attribute values are queried from memory or external sources will bias value construction and choice processes because the recall of initial attributes reduces the accessibility of subsequent attributes. Although the current data cannot be used to directly address the question, future experiments may address the important mechanistic question of whether memory retrieval is a driving factor in the consideration onset asynchronies revealed by the separate attribute consideration onset tDDM.

Despite open questions about the relationship between memory and relative starting times, our finding that attribute consideration start times are asynchronous lends strong support to the idea that choices are made based on comparisons of both separate attribute values as well as overall option values. Hunt and colleagues[11] demonstrated that a hierarchical sequential sampling process that operates over both separate attribute and overall option values explains risky choice behaviour and brain activity better than models operating only on integrated values. Reeck and colleagues[10] showed that individual variation in temporal discounting can be explained by patterns of information acquisition that support attribute-wise or option-wise comparisons. Moreover, their study showed that an experimental manipulation that promotes attribute-wise comparisons compared with one promoting option-wise comparisons increased the patience level of participants when making choices. Together, these results and others (for example, refs. [27,57]) indicate that attribute-level comparisons play an important role in determining choice outcomes. Hierarchical attribute and option-level comparisons are implicit in our specification of the separate attribute consideration onset tDDM because the choice outcome and RT are determined by a weighted sum of the differences in attribute values. However, we showed that attribute-level comparisons do not all begin at the same point in time, and that the magnitude of the difference in RSTs across attributes influences option-level comparisons and choice outcomes.

Our results raise important questions about how attribute weighting strengths and onset timing jointly influence choice outcomes. How should we interpret choices in which the outcome is determined by the advantage in relative timing as opposed to weighted evidence? Could this be strategic use of cognitive flexibility to align decision-making with current goals or should we consider such outcomes to be mistakes? Traditionally, a weighted combination of all attribute values is assumed to yield the 'correct' choice[60]. If the weighting strength on each attribute is appropriate, then any asynchrony in onset timing could produce suboptimal choices (that is, choices in favour of options with a lower weighted sum over all attribute values than another available alternative). In that sense, it is surprising that we find substantial attribute onset asynchrony in healthy young adults and that, in individuals striving to maintain a healthy lifestyle (that is, the sample recruited for our tDCS experiment), a higher level of asynchrony is associated with better health challenge success. However, this view is predicated on the assumption that the attribute weighting strengths are appropriate for the current goal or context.

Conversely, it is possible that shifts in the timing of attribute consideration can be used to achieve the desired outcome. Suppose that a decision-maker knows (not necessarily explicitly) that her standard attribute weights are inconsistent with her current decision context or goal, and adjusting those weights by the necessary amount is costly or unlikely. In that case, shifting the relative onset timing could be an effective means of reducing effort and improving the chances of making a goal-consistent choice. In other words, altering the relative starting times may be a form of proactive control[61,62]. For example, a decision-maker who goes on a diet may find

it difficult to convince herself that she does not like the taste of ice cream and/or to constantly trade-off this delicious taste against the downsides of excess sugar and fat. An alternative way to bring about health challenge success in this situation may be to adjust the process (or processes) that determine RSTs for healthiness and tastiness and to focus on the healthiness of each alternative option alone for a brief period to forgo extremely unhealthy options (without putting in time or effort to compare taste benefits to health costs).

The use of timing differences as described above would be consistent with at least two existing theories on the role of attention in cognition. First, it is consistent with the idea that rational inattention strategies[63–65] can be employed as a means of reducing effort costs. Specifically, if the time advantage for healthiness is large enough, then one could theoretically decide against eating an unhealthy food before even considering its tastiness and thus not experience temptation or conflict. Second, the idea that distinct processes determine consideration onset times and weights for different attributes is paralleled in theories of emotion and food-craving regulation that posit separate attention deployment and stimulus appraisal steps (for examples, see refs. [35,66,67]). However, we do not yet know whether strategic use of attribute consideration onsets or related processes actually happen or whether adjusting the process determining relative onset times is, in fact, less effortful or more likely to succeed than strategies that attempt to alter the attribute weighting strengths.

Altering the processes that determine the relative onset times could be a means or a result of delaying and reducing attention. However, although we found that both cueing attention to healthiness and having the goal of maintaining a healthy lifestyle (tDCS sample versus all others) were associated with faster average onset times for healthiness attributes, we do not know yet whether relative onset times can be manipulated as part of a deliberate strategy. It is also important to note that the response to healthiness cues was heterogeneous in the sense that although most participants made healthy choices more often following those cues, some participants changed only attribute weights or only attribute start times in favour of healthy choices rather than both. Further research is needed to understand why individuals responded to these cues in different ways.

The ability to understand or predict how an intervention or policy change will affect choice processes and their outcomes for specific individuals or groups of people is important for any programme hoping to promote behavioural change, for example, in domains such as health, crime or financial stability. Greater knowledge of the cognitive and neural mechanisms that drive choices in specific individuals is an important step towards this understanding[68]. Our findings demonstrate that when a specific attribute begins to influence the decision process—a factor that has been generally neglected—is an important determinant of choice outcomes. They also suggest that examining relative differences in attribute start times may prove useful in understanding why interventions and policies work in some cases (for example, for specific individuals or groups) but not in others, and may help to increase their effectiveness. Overall, the work we present here provides both a concrete advancement in our knowledge of multi-attribute choice processes and a functional set of computational modelling tools that can be applied to extract deeper mechanistic insights from data on choice outcomes and RTs.

Methods

For all datasets in which we relied on published studies, we included the final reported sample in our analyses. For these studies, we describe the methodological details relevant for our analyses and refer the reader to the published papers for any further details. All participants provided written informed consent in accordance with the procedures of the Institutional Review Board of the California Institute of Technology, the Institutional Review Board of the Faculty of Business, Economics and Informatics at the University of Zurich, or the Ethics Committee of the Canton of Zurich. All participants received a flat fee to compensate for their time in addition to the food they chose.

Dataset 1—MRTs. We use the choice and RT data from the study of Sullivan et al.[16] to test the face validity of our time-varying sequential sampling model. These data are openly available at https://osf.io/jmiwn/. All participants in the MRT sample were healthy adults and had no specific dietary restrictions. Before making any choices, they were reminded of the importance of healthy eating by reading a short excerpt from WebMD.com before starting the choice task.

Participants. The experiment was approved by the Institutional Review Board of the California Institute of Technology. Twenty-eight (seven female) healthy adult participants completed the study.

Procedure. Participants were asked to fast for 4 h before the study. They first rated 160 foods for taste and health on a five-point Likert scale with values from −2 (very little) to +2 (very much). After these ratings, participants were asked to read a short text from WebMD.com on the beneficial effect of healthy eating to increase the frequency with which they tried to succeed in health challenges in the subsequent dietary choice task. In the choice paradigm, participants made 280 choices between two foods on the screen (Fig. 1a). The selection ensured that food pairs would equally represent all possible combinations of taste and health ratings. After each block of 40 choices, participants could take a short break. In 240 trials, participants used a computer mouse to answer, while in the remaining 40 trials, they answered with a keyboard. For the mouse trials, participants had to click the 'start' box at the bottom of the screen to initiate the trial. The cursor reappeared after a random waiting period of 0.2–0.5 s. From this point on, participants had to move the mouse continuously towards the food they wanted to select. They were instructed to answer as quickly and accurately as possible. A random fixation time of 0.4–0.7 s separated the trials. For the keyboard trials, participants selected food items by pressing the left or right choice keys. At the end of the study, one randomly selected trial was paid out, and participants were asked to stay in the laboratory for 30 min or until they had eaten their obtained food.

Dataset 2—GFC. Data for this behavioural GFC study were collected from the same individuals in two testing sessions 2 weeks apart. The two sessions were run on the same weekday and daytime in a 2-h visit in the afternoon. Participants in this study were healthy and did not have any specific dietary restrictions. During the study, they chose naturally and were neither reminded about eating a healthy diet nor encouraged to eat healthy in any way.

Participants. The study was approved by the Institutional Review Board of the University of Zurich's Faculty of Business, Economics and Informatics. Thirty-seven participants (17 female, age = 22.6 ± 3 years (mean ± s.d.)) were included in this study. A prescreening procedure ensured that all participants regularly consumed sweets and other snack foods and were not currently following any specific diet or seeking to lose weight. All participants were healthy and had no current or recent acute illness (for example, cold or flu) at the time of the study. All participants complied with the following rules to ensure comparability across the study sessions: they got a good night's sleep and did not consume alcohol the evening before the study. On the study day, they took a photograph of the small meal that they consumed 3 h before the appointment, and sent this photo to the experimenter. One day before the second study session, participants received a reminder about the rules (described above) and were asked to consume a small meal before their second appointment that was equivalent to their meal before the first test session. Participants received CHF37.5 (~US$39) for each session.

Procedure. Participants were asked to eat a small meal of approximately 400 calories 3 h before their appointment and to consume nothing but water in the 2.5 h before the study started. In the laboratory, participants first rated 180 food items for taste and health. They then made 150 food choices, one of which was randomly selected to be received at the end of the experiment. For each trial, the screen showed two foods next to each other, and participants chose the food they wanted to eat using a four-point scale, picking either 'strong left', 'left', 'right' or 'strong right' (Fig. 1b). The pairing order and positions of the foods on the screen (left versus right) were completely randomized, and the allocation algorithm ensured that one of the foods would be rated as healthier than the other. Participants had 3 s to make their choice, with a jittered interval of 1–3 s of fixation between trials. Between blocks of dietary decisions, participants played a game in which they had to guess cards for monetary rewards. We ignored the card guessing choices for the analyses presented here. At the end of the experiment, participants stayed in the laboratory for an additional 30 min, during which they ate the food they obtained during the study. Note that participants on the second day saw a new set of choice options that was created based on the taste and health ratings they gave on that second day, using the same allocation algorithm as in session one.

Dataset 3—IACs. To determine how attention cues affected attribute timing and weighting, we reanalysed data from Hare et al.[18]. Participants in this study were not following a specific health or dietary goal in their everyday life, but received a cue to think about the healthiness or tastiness of the foods before deciding on a subset of choices in the study.

Participants. The study was approved by the Institutional Review Board of the California Institute of Technology. Thirty-three participants (23 female, age 24.8 ± 5.1 years (mean ± s.d.)) were included. Screening ensured that they were not currently following any specific diet or seeking to lose weight. All participants were healthy, had no history of psychiatric diagnoses or neurological or metabolic illness, were not taking medication, had normal or corrected-to-normal vision, and were right-handed.

Procedure. Participants were instructed to fast and drink only water in the 3 h before the study. In this experiment, participants made a series of 180 choices within a magnetic resonance imaging (MRI) scanner while blood-oxygenation-level-dependant functional MRI was acquired. The experiment had 3 conditions with 60 trials each that were presented in blocks of 10, with the order of blocks and foods shown within blocks fully randomized for each participant. Each food was shown only once (Fig. 1c). In condition one, participants were asked to attend to the tastiness of the food when making their choices, in the second condition, to attend to the healthiness of the food, and in the third condition, to choose naturally. The instructions emphasized that participants should always choose what they preferred to eat regardless of the attention and consideration cues. Before each block, the attention condition cue was displayed for 5 s. For each choice trial, participants had 3 s to answer and were shown feedback on their choice for 0.5 s after responding. Trials were separated by a variable fixation period of 4–6 s. Most participants responded on a four-point scale of 'strong yes', 'yes', 'no' or 'strong no' to indicate whether they preferred to eat or to not eat the food shown on the current trial. Five out of 33 participants completed a version of the task that included a fifth option that allowed them to signal indifference between eating and not eating the food. We followed the original analysis procedures in the IAC study and analysed all 33 subjects as one set. After the scan, participants rated the 180 food items for taste (regardless of health) and health (regardless of taste), with the order of rating types randomized across participants. After both the choice task and ratings were complete, one trial from the choice task was randomly chosen to be realized. Participants were required to eat the food if they answered 'yes' or 'strong yes'. If they answered 'no' or 'strong no', they still had to stay in the laboratory for the 30-min waiting period; however, they were not allowed to eat any other food. Participants were fully informed of these choice incentivization procedures before beginning the study.

Dataset 4—tDCS study. All participants in this study were prescreened during recruitment to ensure that they were actively following a healthy lifestyle. They were specifically asked if they would agree to do their best to choose the healthier option whenever possible on the day of the study. Participants who indicated that they would not do so were still allowed to complete the experiment and were reimbursed for their time, but we did not analyse their data. All participants received a flat fee of CHF100 (~$104).

The procedures for this study were originally described in ref. [69]. We repeat that description here to make this paper self-contained.

Participants. The Ethics Committee of the Canton of Zurich approved the study protocol and all participants provided written informed consent. In total, 199 participants were enrolled in the study. No participants reported any history of psychiatric or neurological conditions or had any acute somatic illness. Participants were prescreened in telephone interviews to ensure they did not suffer from any allergies, food intolerances or eating disorders. To ensure that the snacks in the food choice task would present a temptation, participants were only eligible if they reported regularly consuming snack foods (at a minimum two to three times per week) while at the same time trying to maintain an overall balanced and healthy diet.

Data from 25 participants were excluded because they failed to meet a priori inclusion criteria or data quality checks. Within the study, we requested a written statement of compliance with a health goal for the time of the experiment (see below). Seven men and one woman indicated that they would not comply with the health goal; their data were excluded from all analyses. Note that these participants still completed the experimental procedures and received the same compensation through food and monetary incentives as those who complied, so there was no incentive for the participants to lie about following the health goal. Data from eight participants had to be excluded because they confused the response keys or forgot the identity of the reference item during the task. Four participants were excluded on site due to safety precautions regarding tDCS. Three participants were excluded on site because a re-check of the inclusion criteria revealed that they did not actually like snacks or only consumed them on one to two occasions per month instead of the minimum two times per week. One additional participant had to be excluded because the choice set could not be constructed due to the fact that he reported only the most extreme values on all health and taste ratings. Last, data from one participant was excluded because she never made a healthy choice when taste and healthiness were in conflict in the baseline condition, precluding inference about within-subject changes due to stimulation. This left 87 men and 87 women in the final dataset.

Participants were randomly allocated to stimulation conditions. The anodal (58 participants, 30 female), cathodal (57 participants, 30 female) and sham (59 participants, 27 female) stimulation groups did not differ from each other with regard to age, body mass index or self-reported eating patterns (as assessed by the "three factor eating" questionnaire, German validated version by Pudel and Westenhöfer[66]) (Supplementary Table 9). The groups also did not differ with regard to impulse control (in the stop signal reaction time), working memory capacity (digit span test) or time discounting preferences. Finally, the groups did not differ in the level of hunger that they reported before the choice task (Supplementary Tables 10–17).

tDCS stimulation protocol. The target electrode (5 × 7 cm) was placed on the left dlPFC (Supplementary Fig. 2). The reference electrode (10 × 10 cm) was placed over the vertex, off-centred to the contralateral side in such a way that a 5 × 7-cm area of the reference electrode was centred over the vertex while the remaining area was placed more to the right side. The target electrode covered the two dlPFC regions depicted in Supplementary Fig. 2 (MNI peak coordinates = (−46, 18, 24) and (−30, 42, 24)). These targets were selected because they both showed greater activity for health challenge success > failure in two previous functional MRI studies[51,53]. The coordinates for both the dlPFC and the vertex were identified using a neuronavigation system (Brainsight, Rogue Research, RRID:SCR_009539, https://www.rogue-research.com/; see Supplementary Fig. 2) from individual T1-weighted anatomical MR images for each participant. We applied anodal, cathodal or sham tDCS over this dlPFC site using a commercially available multichannel stimulator (neuroConn). Between a ramp-up and ramp-down phase of 20 s, active stimulation with 1 milliampere (mA) took place for 30 min (anodal and cathodal group) or 5 s (sham). Sham stimulation was delivered with either the anode or the cathode over the dlPFC, counterbalanced over the entire sham group. Both the participants and the experimenters mounting the tDCS electrodes were blind to the stimulation condition.

Procedure. Participants first rated 180 food items for health and taste. They were instructed to rate taste regardless of the healthiness and vice versa for each of our 180 food items on a continuous scale that showed visual anchor points from −5 (not at all) to +5 (very much). Before or after these ratings, participants completed a battery of control tasks in a randomized order. All control tasks were performed both before and after stimulation: a stop signal reaction time task, a self-paced digit span working memory test and a self-paced monetary inter-temporal choice task. To test for stimulation effects on taste and health ratings, participants also re-rated a subset of foods after stimulation (see Supplementary Results).

After all pre-stimulation tasks had been completed, but before any food choices were made, we asked participants to sign a health goal statement in which they indicated whether they would commit to maintaining a health goal during the subsequent food choice task (see Supplementary Methods for an English translation of the health goal text). Participants indicated that they would or would not commit to the goal, dated and signed the document, and then handed it back to the experimenter. Participants could not see which option others in the room had selected, and the experimenter randomizing the tDCS conditions was blind to the responses of the participants to the health goal.

Immediately before beginning the food choice task, participants indicated their current hunger levels. They then completed a series of food choices. The first 101 participants made 60 food choices at baseline; however, we increased the number of baseline choices to 80 for the final 98 participants to have an even number at baseline and under stimulation. All other experimental factors were kept the same for all 199 participants. The baseline choices allowed us to make within-subject comparisons of health challenge success before and during stimulation. Once participants had finished making the baseline choices, stimulation was applied. Participants did not make any choices for the first 3 min of stimulation to allow the current to stabilize. Following the stabilization period, they completed another set of food choices ($n = 120$ for participants 1:101 and $n = 80$ for participants 102:199). No choice pairs were repeated between the baseline and stimulation choice sets. However, the difficulty in terms of taste difference was balanced across the two choice sets (Supplementary Information).

Participants completed the set of food choices under stimulation (or sham) in a maximum of 16 min. In the remaining 8–14 min of stimulation (or sham) time, participants completed several control tasks. We randomized the order of the post-stimulation control tasks so that all tasks had an equal chance of being run in the period when current was still being applied versus the 5–10-min window immediately after stimulation (during which physiological after effects of the tDCS were still present, see refs. [70,71]). Once they had completed all post-stimulation control tasks, participants filled in a questionnaire battery (the three factor eating questionnaire, the cognitive reflection test, the 'Big Five' personality dimensions and socioeconomic status). They also indicated whether and to what degree they had tried to comply with the health goal throughout the study, whether they had felt the stimulation and how strongly, and whether they had any problems understanding or following the instructions. Finally, participants received and ate their selected food 30 min after they made their final decision in the food choice task.

Food choice paradigm. Participants were asked to eat a small meal of ~400 kcal 3 h before the study and consume nothing but water in the meantime. In the health challenge paradigm, participants chose which food they wanted to eat at the end of

the study. To comply with their health goal, they had to choose the healthier item as often as they could. However, the paradigm was engineered such that health and taste of the food options always conflicted based on the ratings of the participant, so that they would always have to forgo the tastier food to choose healthy. Participants knew that one of their choices would be realized at the end, and they would have to eat whatever they chose on the trial that was randomly selected.

Participants were shown the picture of a reference food for 3 s at the beginning of each block. This reference food was either healthier and less tasty than all ten items shown in the upcoming block or tastier and less healthy than all ten upcoming items. For each of the ten trials within a block, participants had to decide whether they preferred to eat the food currently shown on the screen or the reference food at the end of the study. The identity of the reference food was written in text on the screen so that participants did not need to remember it (Fig. 1d). During each choice trial, participants had 3 s to make their decisions, and each trial was separated by a jittered inter-trial interval of 2–6 s. One trial was selected at random to be realized after all experimental procedures were completed. At the end of the study, participants stayed in the laboratory for 30 min to eat the food they obtained in the study.

Statistical analyses. For all Bayesian modelling analyses, we used the default, uninformative priors specified by the packages brms, BEST or BayesFactor from R (see Supplementary Methods). These analyses are not predicated on assumptions of normally distributed data or equal variances across groups. Throughout the paper, the notation "PP()" indicates the posterior probability that the relation stated within the parentheses is true. Similarly, the BF represents the relative evidence for this relationship over its opposite (for example, greater than zero versus less than zero). Whenever we analysed previously published data, we applied the same subject-level and trial-level exclusion criteria described in the original papers.

tDDM with separate attribute consideration onset times. We fit a DDM that allowed for differential onset times for taste and health attributes during evidence accumulation to choice outcome and reaction time data of participants. Several of the food choice tasks used a four-point decision-strength scale, and for these data, we collapsed choices into a binary yes/no or left/right choice. The following six free parameters were separately estimated for each participant and condition:

Thr: the evidence threshold for responding (symmetric around zero).

Bias: the starting point bias for the evidence accumulation process (zero = no bias).

nDT: the non-decision time and corresponds to the starting time for taste in our model.

RST: the relative start time for health (timing is relative to the start of taste processing; positive values mean that health enters the process after taste, negative values mean health enters before taste).

ω_{taste}: the weighting factor determining how much taste contributes to the evidence accumulation rate.

ω_{health}: the weighting factor determining how much healthiness contributes to the evidence accumulation rate.

The values of these six parameters were used to simulate choices and RTs using the sequential sampling model described in the equation below to update the relative evidence level at each subsequent time step t.

If taste enters first, the evidence-updating equation is as follows:

$$E_t = E_{t-1} + \left(\omega_{taste} \times TD + \left(t > \left|\frac{RST}{dt}\right|\right) \times \omega_{health} \times HD\right) \times dt + noise \quad (1)$$

While if healthiness enters first it is as follows:

$$E_t = E_{t-1} + \left(\left(t > \left|\frac{RST}{dt}\right|\right) \times \omega_{taste} \times TD + \omega_{health} \times HD\right) \times dt + noise \quad (2)$$

Thus, the times at which the weighted value differences in tastiness and healthiness attributes ($\omega_{taste} \times TD$ and $\omega_{health} \times HD$, respectively) begin to influence the evidence accumulation rate are determined by the RST. When the conditional statement $\left(t > \left|\frac{RST}{dt}\right|\right)$ is false, it equals 0, while if true, it equals 1. Multiplying one of the two weighted attribute values by 0 until $\left(t > \left|\frac{RST}{dt}\right|\right)$is true means that that attribute does not factor into the evidence accumulation process for the initial time period determined by |RST|. The RST parameter is defined as the consideration start time for healthiness minus the starting time for tastiness. Thus, RST will have a positive value when tastiness enters consideration first and a negative value when healthiness is considered first. Note that the standard, synchronous onset DDM is equivalent to the specific case of RST = 0, and then equations (1) and (2) are equivalent because t is always greater than (|RST/ t|) and $\left(t > \left|\frac{RST}{dt}\right|\right)$ always equals 1.

Based on previous mouse-tracking results from Sullivan et al.[16], our model formulation makes the simplifying assumption that once an attribute comes into consideration, it continues to influence the rate of evidence accumulation until the choice is made. Model comparisons testing this assumption showed that the different starting time formulation fit the data better than DDMs that allowed for differential attribute consideration end times, both different start and end times, non-decision times that varied as a function of choice outcome or starting point biases in favour of tastiness (Figs. 2 and 3; Extended Data Fig. 2; Supplementary Table 1).

Evidence accumulation proceeds according to equation (1) or (2) in the following manner. The evidence accumulation process begins with an initial value (E_0) that is equal to the value of the Bias parameter. This value is then updated in discrete time steps of $dt = 0.008$ s until $|E_t|$ is greater than the Thr parameter value. The noise at each step of the accumulation process is drawn from a Gaussian distribution with mean = 0. The differences in taste and healthiness ratings between Food 1 and Food 2 (or Food 1 versus 0 for the single-item choices in the IAC dataset) on a given trial are denoted by TD and HD, respectively. Once the threshold is crossed, the RT is computed as $t \times dt + nDT$, where nDT is a free parameter for a non-decision time that accounts for the time required for any initial perceptual or subsequent motor processes that surround the period of active evidence accumulation and comparison.

We estimated the best values for all six free parameters described above separately for each participant and condition using the differential evolution algorithm described in Mullen, et al.[72], with a population size of 60 members run over 150 iterations. For every iteration, we simulated 3,000 decisions and RTs for all unique combinations of taste and healthiness trade-offs in the choice set for each participant using the six tDDM parameters for each population member. We then computed the likelihood of the observed data given the distribution generated by the 3,000 simulated choices for a given set of parameters. For each subsequent iteration, the population evolves towards a set of parameters that maximize the likelihood of the observed data using the procedures described by Mullen and colleagues[72]. We examined the evolution of the population over the 150 iterations and generations and found that the differential evolution algorithm settled on a set of best-fitting parameters well before 150 iterations in our datasets. The upper and lower bounds on the search space for each of the six parameters are listed in Supplementary Table 18. The ratings for taste and healthiness were z-scored across all available ratings of each type for the entire set of participants in each study.

Last, we also fit a standard DDM and several other alternative DDM formulations (Supplementary Table 1) to all datasets using the same procedures as the tDDM. The simulated choice sets from each model shown in Fig. 2 were composed of 1,000 repetitions of each of the 673 unique taste and health combinations used across all four datasets.

We also fit the tDDM using two levels of resolution for the tastiness and healthiness ratings in the GFC and tDCS studies. The tastiness and healthiness ratings from these two studies were collected on a 426-point visual analogue scale. We initially fit the tDDM using the 426-point ratings scale. We also estimated the fits after first reducing the resolution to 10 equally sized bins (that is, 42.6 points per bin) for both taste and health. Both versions yielded very similar results, but the estimation proceeded considerably faster when using the binned ratings because this reduced the number of unique combinations of attributes and therefore the number of simulations required for the fitting procedure. We report the parameter values and results from the model with binned ratings for these studies.

Tests of parameter recovery. We generated simulated choices and reaction times by parameterizing the standard DDM and tDDM using the best-fitting parameters for each model estimated from the choices made by the participants in the baseline condition for all four studies. The simulated choice sets were based on these parameters and the tastiness and healthiness differences participants faced during every decision trial. Thus, the simulated choice sets matched the empirical data in terms of trial numbers and attribute difference distributions. Fitting these simulated choices allowed us to quantify the ability of both models to recover known parameter values within the context of our experimental datasets and the ability to distinguish between these models (Extended Data Fig. 1; Supplementary Fig. 1; Supplementary Table 1).

Testing taste versus healthiness influence by RT. In addition to parameter recovery tests, we used simulated choices to test how well each model reproduced choice and RT characteristics observed in the empirical data. A hierarchical Bayesian logistic regression analysis showed that the influence of taste and healthiness on choice outcomes differed as a function of RTs (equation (3); Supplementary Tables 2–4). Specifically, this analysis tested the influence of each attribute on trials in which the response was made before versus after the relative-starting-time advantage of the first attribute had on average elapsed. The population-level regressors are listed in equation (3) below.

$$\begin{aligned} Left = {} & \beta_0 + \beta_1 HFirst + \beta_2 InitAdv + \beta_3 TD + \beta_4 HD + \beta_5 HFirst \times InitAdv \\ & + \beta_6 HFirst \times TD + \beta_7 HFirst \times HD + \beta_8 InitAdv \times TD + \beta_9 InitAdv \times HD \\ & + \beta_{10} HFirst \times InitAdv \times TD + \beta_{11} HFirst \times InitAdv \times HD + e \end{aligned} \quad (3)$$

In this equation, Left is a binary indicator of the choice outcome. HFirst is a dummy variable (1 = healthiness, 0 = taste) indicating which attribute is considered first (as determined by the tDDM). InitAdv is a dummy variable (1 = before, 0 = after) indicating whether the response was made before the median value of the sum of

RST difference plus non-decision time across participants had elapsed. This sum was equal to 1 s. One second was also the cut-off for the first quartile of the RT range, meaning that 25% of choices were made in 1 s or less. The abbreviations TD and HD stand for the differences in tastiness and healthiness, respectively, for each trial. Subject-specific coefficients were estimated for all regressors except HFirst because each participant had only one level of that regressor in his or her baseline condition.

We computed this regression using four different subsets of empirical or simulated data. Initially, we analysed the baseline choice trials pooled over all four studies (baseline = mouse response trials from MRT, day 1 trials from GFC, no-cue trials from IAC, pre-stimulation trials from tDCS). We then compared this model to two simpler models that omitted either (1) the dependency on RT (that is, InitAdv dummy variable) or (2) both the dependency on RT and the indicator for which attribute a participant considered first (that is, InitAdv and HFirst dummy variables). The full model explained the data better (Supplementary Table 4); therefore, we used it to examine choice patterns generated by the standard DDM and tDDM. The means and 95% HDIs for regression coefficients plotted in Fig. 3a are derived from estimating the hierarchical logistic regression in equation (3) to observed, time-varying (tDDM), standard (sDDM) or tastier starting-point-bias (bDDM) model-simulated choices for all participants in whom the |RST| parameter fell into the third quartile. We subset the data into this quartile so that timing differences between taste and healthiness would be big enough to have a clear effect in both the real and simulated data.

Correspondence of tDDM health delay estimates with MRT estimates. With their MRT analysis, Sullivan and colleagues[16] were able to estimate to within a fraction (1/101) of each RT when health first became and remained significant in each choice (see Fig. 4b in that study). To compare our estimate (which is given in seconds and represents a mean value across all a given set of choices) to the MRT estimates, we also transformed the MRT estimates of start times for health into a mean estimate in seconds. Specifically, we took the mean of the estimated trial-wise health start time bins for each participant and multiplied it by the mean RT of the participants, then divided by 101. The MRT method was only able to estimate health start times for $n = 18$ out of 28) participants; therefore, we calculated the Bayesian equivalent of Pearson's correlation coefficient between tDDM and mouse-tracking estimates of health start times in this subset of participants. Unless otherwise noted, all correlation coefficients reported in this paper represent the mean of the posterior distribution from a Bayesian correlation analysis. These Bayesian correlations were implemented in R and JAGS based on code published at http://doingbayesiandataanalysis.blogspot.com/2017/06/bayesian-estimation-of-correlations-and.html, which accompanies the book by Kruschke[73].

Relationship between RSTs and other tDDM parameters. To explain how individual differences in the RST for healthiness were related to the other tDDM parameters (Supplementary Table 6), we estimated the model specified in equation (4) below:

$$\begin{aligned}\mathrm{RST} = {} & \beta_0 + \beta_1\omega_{\mathrm{taste}} + \beta_2\omega_{\mathrm{health}} + \beta_3\mathrm{nDT} + \beta_4\mathrm{Thr} + \beta_5\mathrm{bias} + \beta_6 \\ & \mathrm{study\,IAC} + \beta_7\mathrm{study\,MRT} + \beta_8\mathrm{study\,tDCS} + \beta_9\mathrm{bias}\times\mathrm{study\,IAC} + \beta_{10} \\ & \mathrm{bias}\times\mathrm{study\,MRT} + \beta_{11}\mathrm{bias}\times\mathrm{study\,tDCS} + e\end{aligned} \tag{4}$$

Note that we interacted the bias parameter from the tDDM with a dummy variable indicating the study because the bias measures different answers across studies given the task designs (for example, left/right, eat/do not eat). The GFC study served as the baseline in this regression.

Out-of-sample tests for comparing the standard DDM and tDDM. We fit the standard DDM and tDDM with separate attribute consideration onsets to the odd-numbered choices from each participant and then compared the accuracy of the two models when predicting even-numbered choice outcomes. We used the squared error in predicting choice outcomes as our measure of accuracy[74]. The predicted outcome for each choice was computed as the mean outcome over 1,000 simulations from the standard DDM and tDDM. Choices for the food on the left or to eat the food in single-option decisions were set to a value of 1, and the alternative choice was set to a value of 0. Thus, the mean outcome from the 1,000 simulations for each choice represented the probability of a given outcome. The scoring rule for accuracy on each trial was then computed as: (True outcome – Prediction)^2. We computed the squared error separately for tastier and less tasty choice outcomes and then took the mean error across these trials types to obtain a measure of balanced error.

Changes in tDDM parameters between instructed attention conditions. We compared tDDM parameters fit to choices during HC, TC and NC blocks using a Bayesian *t*-like test (implemented in the R package BEST v.3.1.0)[75], which in turn relies on JAGS (v.3.3.0).

Modelling changes in behaviour under tDCS. We first fit the hierarchical regression model specified in equation (5) to the odd-numbered baseline trials in our tDCS dataset. Based on those fitted parameters, we generated predictions about the probability of health challenge success in even-numbered trials as a function of tDCS polarity (anodal, cathodal, sham), stimulation session (baseline, active), health difference, taste difference and participant identity. We then estimated equation (5) on all even-numbered trials for which the probability of health challenge success was predicted to be between 0.2 and 0.8.

To examine whether stimulation over the left dlPFC caused changes in health challenge success, we fit a Bayesian hierarchical logistic regression model to the tDCS dataset. The population-level regressors for this model are given in condensed notation in equation (5).

$$\begin{aligned}\text{Health challenge success} = {} & \beta_0 + \beta_1\mathrm{TD} + \beta_2\mathrm{HD} + \beta_3\text{stimulation on} + \\ & \beta_4\text{cathodal} + \beta_5\text{anodal} + \beta_6\mathrm{TD}\times\text{stimulation on} + \beta_7\mathrm{HD}\times\text{stimulation on} + \beta_8 \\ & \mathrm{TD}\times\text{cathodal} + \beta_9\mathrm{TD}\times\text{anodal} + \beta_{10}\mathrm{HD}\times\text{cathodal} + \beta_{11}\mathrm{HD}\times\text{anodal} + \beta_{12} \\ & \text{stimulation on}\times\text{cathodal} + \beta_{13}\text{stimulation on}\times\text{anodal} + \beta_{14} \\ & \mathrm{TD}\times\text{stimulation on}\times\text{cathodal} + \beta_{15}\mathrm{TD}\times\text{stimulation on}\times\text{anodal} + \beta_{16} \\ & \mathrm{HD}\times\text{stimulation on}\times\text{cathodal} + \beta_{17}\mathrm{HD}\times\text{stimulation on}\times\text{anodal} + e\end{aligned} \tag{5}$$

Here, TD and HD denote the absolute value of taste and healthiness, respectively, difference between foods for each trial, stimulation on is a dummy variable taking the value 1 under stimulation and 0 at baseline, and anodal and cathodal are the active stimulation conditions. The sham condition is the baseline in this regression. The model included the main effects of all regressors as well as the two-way and three-way interactions between attribute differences and stimulation type and session (that is, baseline versus stimulation on). The model also included subject-specific intercepts, stimulation effects and slopes for HD and TD (Supplementary Table 8).

Choice of sample sizes, randomization and blinding. The IAC and MRT studies were based on preexisting datasets and we included the participants analysed in the original papers. No statistical methods were used to predetermine sample sizes for the GFC study and tDCS studies, but our sample sizes were similar to those reported in relevant previous publications[18,38,51]. For the tDCS study, participants were randomly assigned to the stimulation condition. Experimental conditions in the tDCS and GFC studies were blocked. For the tDCS study, the baseline condition was always presented first to prevent any influence of potential tDCS after-effects. The food choice and gambling conditions in the GFC study were presented in random order. Data in the tDCS study were collected double-blind. Data analyses were performed with knowledge of the condition labels in all experiments.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

The data analysed in this paper are openly available on the Open Science Framework at https://osf.io/g76fn/. Additional data for the MRT experiments from Sullivan et al.[16] are available at https://osf.io/jmiwn/.

Code availability

The code for fitting the diffusion models and running the other analyses is openly available on the Open Science Framework at https://osf.io/g76fn/.

Received: 9 November 2018; Accepted: 4 May 2020;
Published online: 1 June 2020

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Acknowledgements

This study has been supported by Swiss National Science Foundation (SNSF) grants 320030_143443 and 32003B_166566 (to C.C.R. and T.A.H.), a Marie Curie International Incoming Fellowship PIIF-GA-2012-327196 (to A.R.B.) and EU FP7 grant 607310 (to T.A.H.). C.C.R. received support from the SNSF (grant no. 100019L_173248) and from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No 725355, BRAINCODES). The funders had no role in the conceptualization, design, data collection, analysis, decision to publish or preparation of the manuscript. The authors thank A. Makwana and A. Cubillo for contributing code for the food choice and control tasks, J. Price for help with data collection and documentation, and G. Lombardi for help with data collection and documentation as well as useful discussions about analysis strategies and implementation.

Author contributions

S.U.M., A.R.B., R.P., C.C.R. and T.A.H. designed one or more aspects of the research. S.U.M. and A.R.B. collected the novel data for the GFC and tDCS studies. R.P. and T.A.H. designed the tDDM with separate attribute consideration onset times. S.U.M., A.R.B., R.P. and T.A.H. analysed the data. S.U.M., A.R.B., R.P., C.C.R. and T.A.H. wrote the paper.

Competing interests

The authors declare no competing interests.

Additional information

Extended data is available for this paper at https://doi.org/10.1038/s41562-020-0893-y.

Supplementary information is available for this paper at https://doi.org/10.1038/s41562-020-0893-y.

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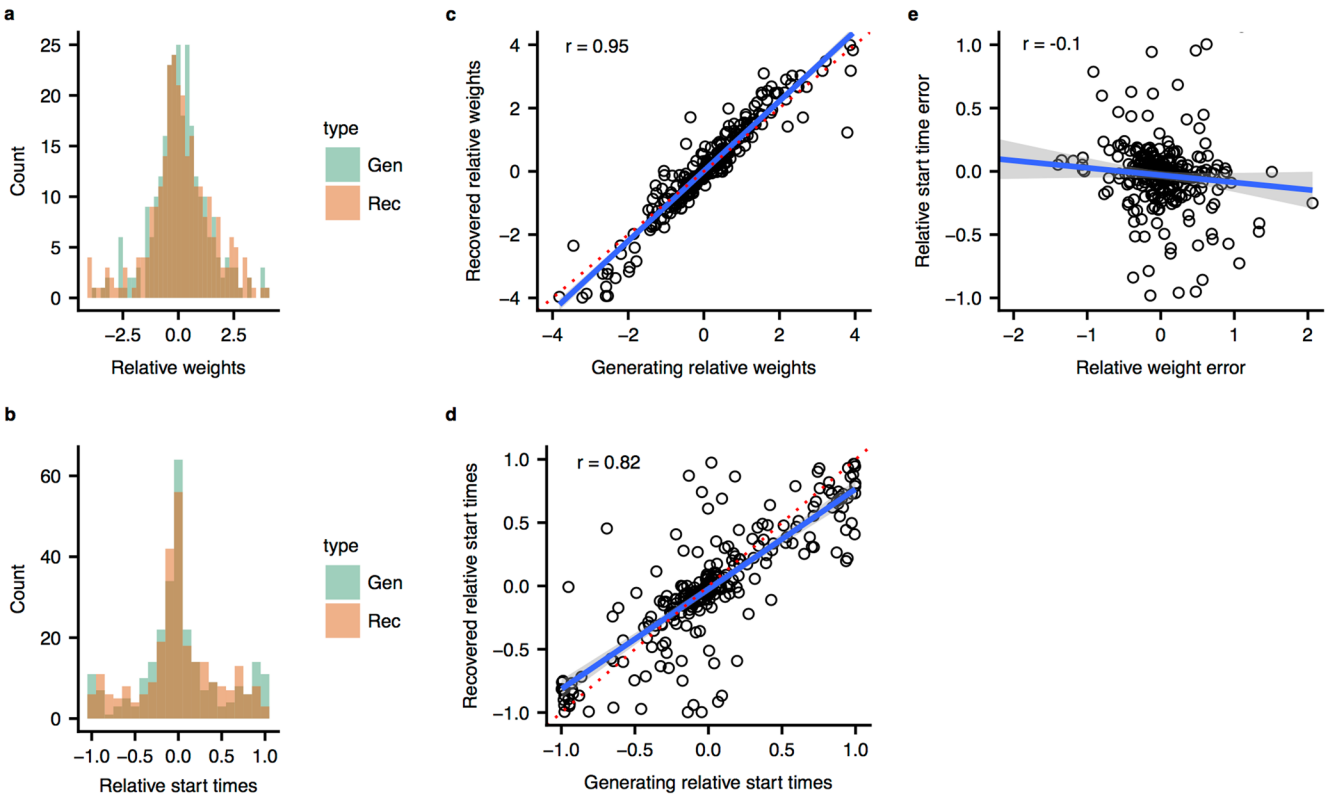
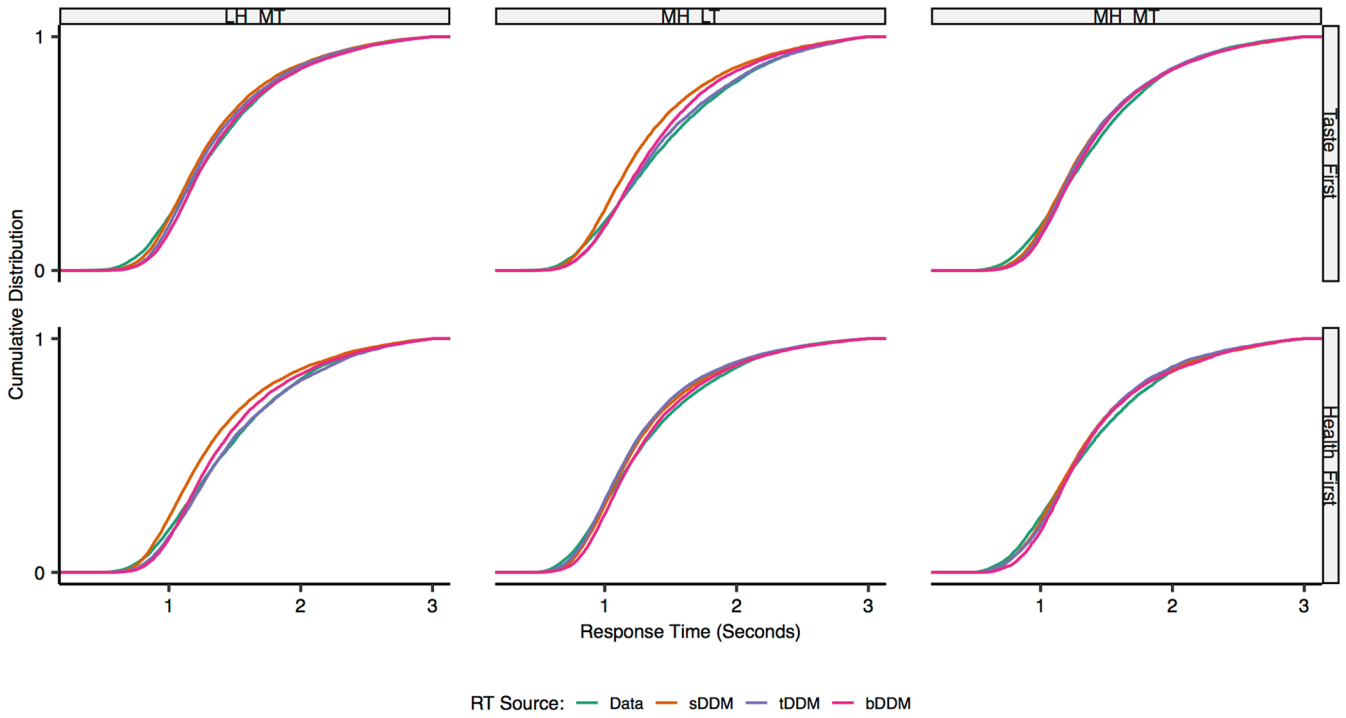
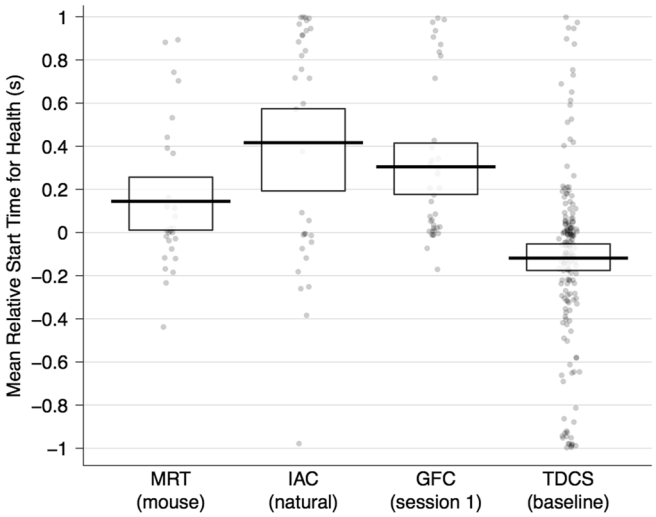
Peer review information Primary Handling Editor: Marike Schiffer



Extended Data Fig. 1 | Parameter recovery for the time-varying DDM. Parameter recovery for the time-varying DDM with separate consideration onset times for tastiness and healthiness attributes. The plots in the first column show the distributions of all 272 generating and recovered relative weighting (**a**) and timing parameters (**b**). There was no significant difference between generating and recovered relative weighting (mean difference = 0.01, 95% HDI = [−0.36, 0.54], posterior probability of a difference > 0 = 0.662, Bayes factor = 0.140) or relative timing parameters (mean difference = −0.01, 95% HDI = [−0.03, 0.01], posterior probability of a difference > 0 = 0.105, Bayes factor = 0.024). The panels in the second column show the correlations between the generating and recovered relative weighting (**c**) and timing parameters (**d**). The red dotted line indicates the x = y identity line. Panel **e**) plots the error in relative weight recovery against the error in relative timing recovery. This plot shows that there is no significant correlation between the two types of error when fitting the model (r = − 0.1, 95% HDI = [−0.215; 0.018], posterior probability of observing a negative correlation = 0.95). The grey shaded area (panels c-e) signifies the 95% confidence interval.



Extended Data Fig. 2 | Cumulative response time distributions for sDDM, tDDM and bDDM. Cumulative distributions for response times by participant type, choice outcome and data source. Participants estimated to consider taste or health first are plotted in the top and bottom rows, respectively. Response times for choices in favour of (91) less healthy but more tasty (LH_MT), (2) more healthy but less tasty (MH_LT), or (3) both more healthy and more tasty (MH_MT) outcomes are shown in columns 1-3, respectively. Choices in favour of the option rated as less healthy and less tasty were rarely made (less than 5% of trials) and are omitted for clarity. Responses generated by human participants are shown in green lines. Responses generated by simulated agents using the best-fitting sDDM, tDDM, and bDDM parameters are shown in orange, purple, and magenta lines respectively. All three models can recreate the RT patterns in the empirical data equally well when choice outcomes align with the attribute participants consider first. However, the sDDM and bDDM both generate response times that are too fast relative to the empirical data when participants that consider taste first ultimately choose in favour of a more healthy, but less tasty option (row 1, column 2) or if participants that consider health first ultimately choose in favour of a less healthy, but more tasty option (row 2, column 1). In contrast, the tDDM is able to reproduce the observed response time distributions in these cases well.



Extended Data Fig. 3 | Relative start time for all participants in each dataset. Relative start times in seconds for healthiness compared to tastiness for all participants in each study. Positive values indicate that tastiness is considered before healthiness and negative values that healthiness is considered before tastiness. In each column every dot is a separate participant. The thick black horizontal bars represent within-study means and the rectangular bands indicate the 95% highest density intervals (HDIs). Dataset abbreviations: MRT = data from the computer-mouse response trials in Sullivan et al 2015; IAC = data from the natural choice condition in Hare et al 2011; GFC = newly collected data from the first session/day of an experiment combining gambles and food choices; TDCS = newly collected data from the pre-stimulation baseline choices in our tDCS experiment.

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Last updated by author(s): Apr 16, 2020

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☒	☐	For null hypothesis testing, the test statistic (e.g. *F*, *t*, *r*) with confidence intervals, effect sizes, degrees of freedom and *P* value noted *Give P values as exact values whenever suitable.*
☐	☒	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☐	☒	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☐	☒	Estimates of effect sizes (e.g. Cohen's *d*, Pearson's *r*), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	Data were collected with Psychophysics Toolbox version 3.0.11 in Matlab.
Data analysis	All analyses were performed with the R, STAN and JAGS software. For all Bayesian modeling analyses, we used the default, uninformative priors specified by the respective R-packages.

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All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A list of figures that have associated raw data
- A description of any restrictions on data availability

The data analysed in this paper are openly available on the Open Science Framework at, https://osf.io/g76fn/. Additional data for the mouse response trajectory experiments from Sullivan et al. (2015) are available at https://osf.io/jmiwn/

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Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	Quantitative experimental study
Research sample	University undergraduate students from California Institute of Technology (datasets Sullivan et al. 2015 (MRT) and Hare et al. 2011 (IAC)), and University of Zurich (datasets GFC and TDCS); no representative samples because we studied basic choice processes that should not vary with demographics; for details on demographics of the 4 different datasets please see the methods section on pages 22-29; the MRT dataset is openly available at: https://osf.io/jmiwn/
Sampling strategy	We randomly invited participants from an established database of research volunteers maintained at the University of Zurich for the newly collected datasets presented in this paper. We originally collected the data on the "gamble plus food choices" task (GFC) to test a hypothesis unrelated to the current paper. We collected data from 30-40 participants according to the common practice for preliminary behavioral experiments in our group. We simply re-used these data to test the accuracy of the model we develop in the current work in predicting choices made by the same participants two weeks apart. We aimed to collect at least 150 participants (i.e. 50 per condition) in our tDCS experiment because we expected the effects of tDCS on food choices to be more variable across participants than in our previous work pairing tDCS manipulations with monetary decisions and using 20-25 participants per condition (Ruff et al., 2013 Science; Raja-Beharelle et al., 2015 J Neuro). We expected greater variability because of the heterogeneity in both food preferences and self-control strategies and ability across individuals. Therefore, we doubled the number of participants per condition relative to our previous work.
Data collection	Data were collected with computerized behavioral paradigms; additional techniques: MRT used mouse-tracking as additional technique, the IAC dataset was collected while participants were undergoing fMRI, and the TDCS dataset was collected before and during transcranial direct current stimulation. No one besides the researcher(s) and the participants were present. The experiments MRT, IAC, and GFC were conducted without blinding (as there was no need) but fully incentivized to avoid experimenter demand effects, the TDCS experiment was conducted double-blind.
Timing	Information on data collection is not available for the MRT and IAC datasets. They are existing datasets from different teams that we reused in full here. Data were collected in April 2016 for the GFC study. Data for the TDCS study were collected from December 2014 to February 2016 .
Data exclusions	The exclusion criteria described in the Methods section were established a priori for the GFC and TDCS datasets. For the other two re-used datasets, all data utilized in the original publications were included in our current analyses.
Non-participation	No participants dropped out or declined participation.
Randomization	MRT, IAC and GFC did not have treatment groups. Participants for the TDCS study were randomly allocated to the anodal, cathodal and sham stimulation conditions and were blind to the treatment condition. The experimenters giving instructions to and mounting the electrodes on participants' heads were also blind to the participants' stimulation condition.

Reporting for specific materials, systems and methods

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Materials & experimental systems

n/a	Involved in the study
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology
☒	☐ Animals and other organisms
☐	☒ Human research participants
☒	☐ Clinical data

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging

Human research participants

Policy information about studies involving human research participants

Population characteristics	Healthy young adults
Recruitment	Participants in the novel datasets were drawn from a database of research volunteers maintained at the University of Zurich. Registration for this database is advertised with flyers on campus and brief presentations in lectures at the beginning of each term.
Ethics oversight	All participants provided written informed consent in accordance with the procedures of the Institutional Review Board of the California Institute of Technology, the Institutional Review Board of the Faculty of Business, Economics and Informatics at the University of Zurich, or the Ethics Committee of the Canton of Zurich.

Note that full information on the approval of the study protocol must also be provided in the manuscript.