Appendix

Salient Nutrition Labels increase the Integration of Health Attributes in Food Decision-Making

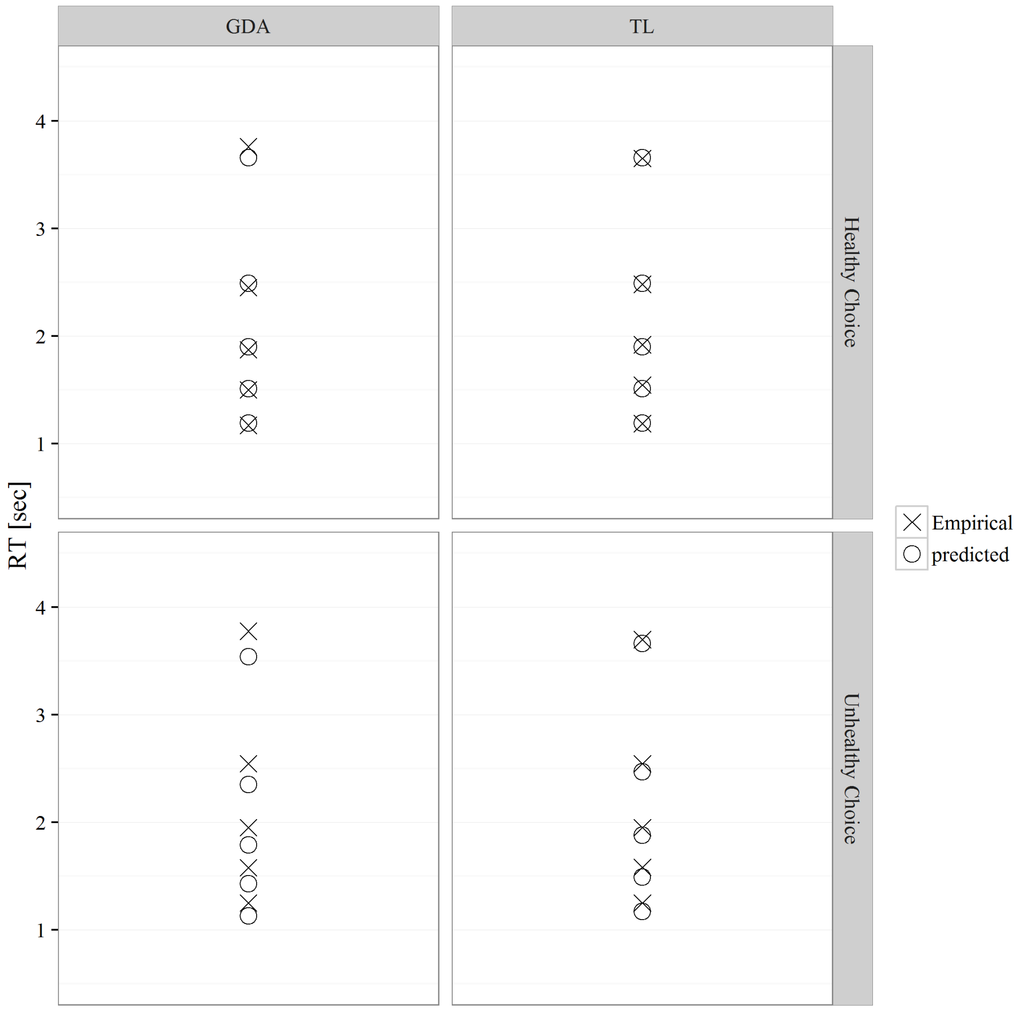

Figure S1. Quantile probability plot for varying drift rates per label across participants.

Additional Analyses

Rating-specifif Drift Rates

We also analyzed the drift rates for the two labels conditional on taste ratings. There is not enough data for rating-specific single-subject fits, so instead we fitted the rating-dependent drift rates at the group level, treating all participants as one. Here, Monte Carlo simulations are not suitable for assessment of model fit, which is why only quantile probability plots are presented. We let the drift rate vary for each rating step for GDA and TL trials separately. Assuming that all participants have the same drift rate constitutes a very stark prediction. Estimating drift rate as well as drift rate variability for each rating bin and label very likely leads to instability in estimation due to the high number (32) of free parameters. Therefore, we only allowed for different drift rates per rating bin and label and estimated the inter-individual variability of drift rates by applying a jackknifing procedure (Dambacher &

Hübner, 2015; Gray & Schucany, 1972; Miller, Patterson, & Ulrich, 1998). In this procedure, a set of parameter estimates is computed for each participant i (i=1, …. , n) by temporarily omitting participant i and fitting the model from the remaining n - i participants (Dambacher & Hübner, 2015). The goal of this procedure is to estimate a parameter of a population of interest from a random sample of data of this population (Abdi & Williams, 2010). This procedure allows inspecting variations in the estimated parameters. A pseudo-value estimation of the n^{th} observation (T^*_n) is computed as the difference between the parameter estimation T obtained from the whole sample (N) and the parameter estimation T_{-n} obtained without the n^{th} observation (N-1) (Abdi & Williams, 2010).

$$T^*_n = N \times T - (N-1) \times T_{-n}.$$

The jackknife estimate and its standard deviation can then be obtained as the mean of the pseudo-values, and the standard error of the pseudo-values, respectively (see (Abdi & Williams, 2010)). Here we used the jackknife median, which is a more robust measure of central tendency that is not unduly affected by outliers (Huber & Ronchetti, 2009) as the median of the pseudo-values. The median absolute deviation of the pseudo-values was used as a robust measure of dispersion (Leys, Ley, Klein, Bernard, & Licata, 2013). Descriptively, the drift rate was higher for TL compared to the GDA label, especially when the unhealthy product was actually preferred, see Figure S2. Also, in line with other studies (Krajbich et al., 2010; Philiastides & Ratcliff, 2013), we find that drift rate varies with overall task difficulty (i.e., across rating bins). See also the quantile probability plot in Figure S3).

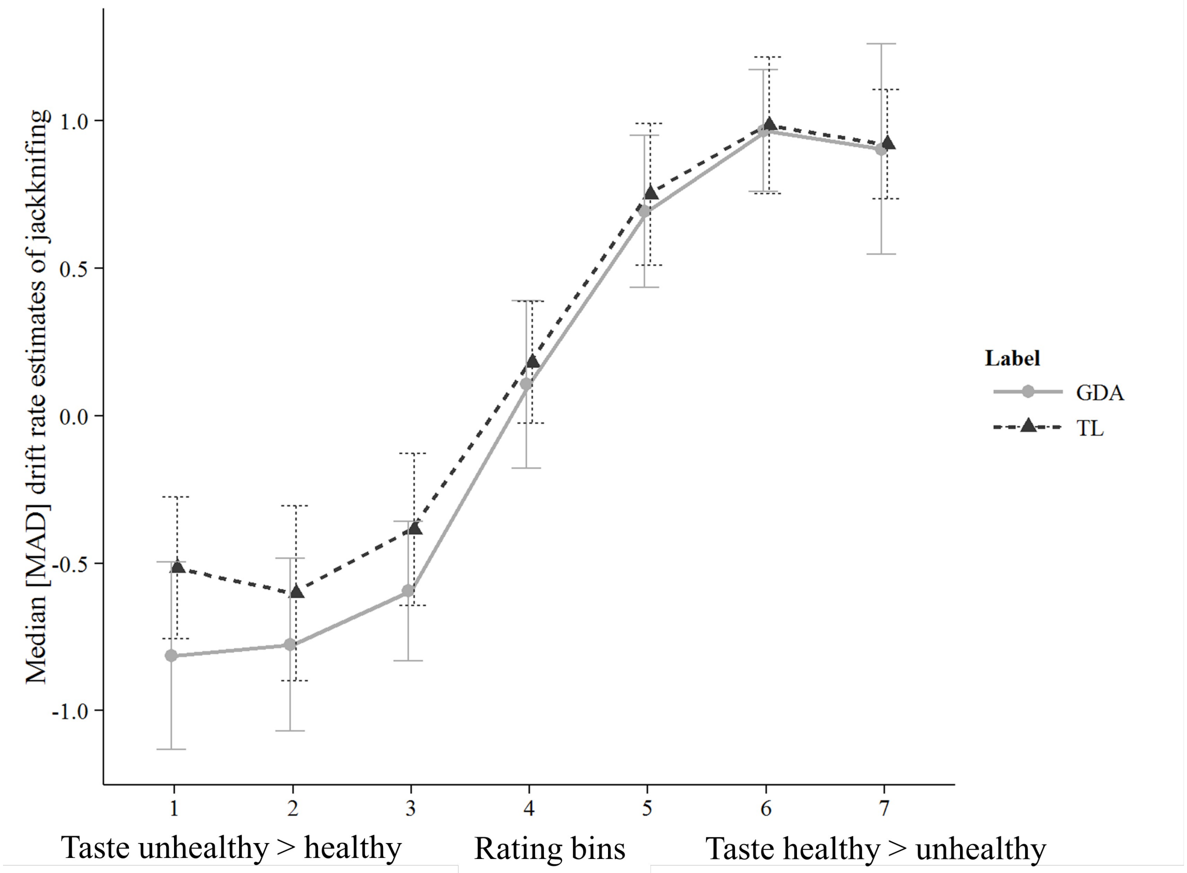

Figure S2. Median drift rate estimates [median absolute deviation] as obtained from the jackknifing procedure described in the main text. Abbreviations: MAD, median absolute deviation.

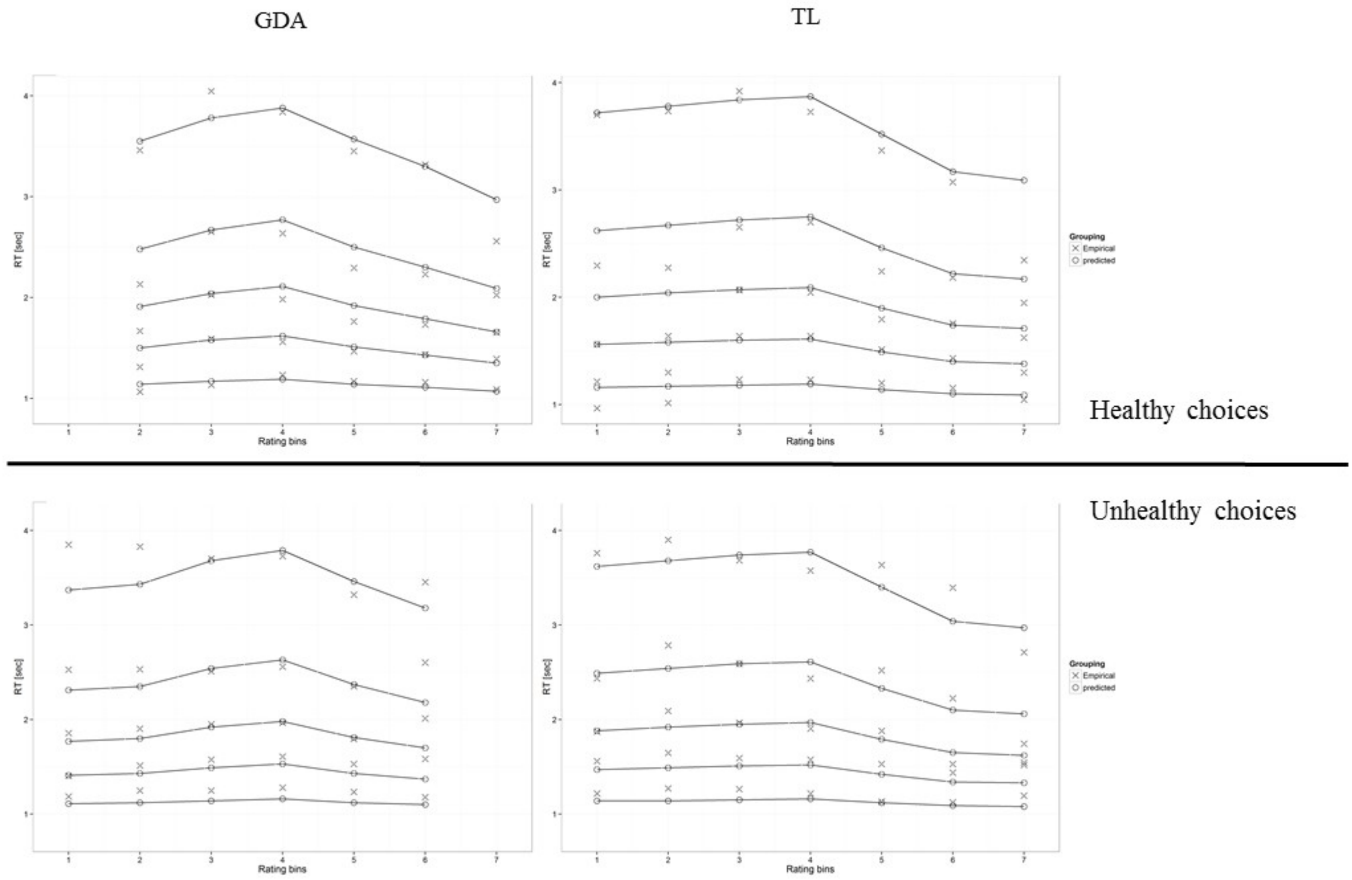

Figure S3. Quantile probability plots for rating-specific drift rates per label across participants.

Weight on Taste and Health

To test whether TL labels increase the absolute weight of health and decrease the absolute weight of taste on subjects' decisions (as opposed to simply changing the relative weight) we ran additional logistic mixed models. For each label we ran a logit regression with only taste (left minus right) predicting choosing the left item, as well as a logit regression with only health (left versus right) predicting choosing the left item. When comparing the coefficients, we can then test whether they decrease for TL in case of taste, and increase in case of health. Indeed, we find that the estimate for taste ratings predicting choice is lower for TL labels (estimate TL: 0.339, estimate GDA: 0.427), while it is higher for health (estimate TL: 0.264, estimate GDA: -0.172).

Additional experiments

We additionally ran two experiments to test whether a simple one-dimensional nutrition label showing only the sugar content would be sufficient to detect a difference between GDA and TL labels. Thus, we again compared TL versus GDA labels, but used labels that were less complex: 44 participants completed experiment 2 (reduced nutrition information, showing only the sugar content of the products, mean age=24.37, *SD*=4.7) and 43 participants completed experiment 3 (reduced nutrition information, showing only the sugar content of the products and additionally without percentages on the GDA labels, mean age=24.74, *SD*=4.4), see Figure S4 for the stimuli used in Experiment 2 and 3. Here, we always compared green versus red labeled products.

Methods

Mixed-effects logistic regression analysis (mixed model “Label” and “Label + Liking”) as detailed in the main text were applied to analyze the effect of label on healthy choices. Also, we applied the drift diffusion model to analyze whether drift rates differ between the two labels (model “Drift” in the main text).

	Healthy product	Unhealthy product
TL label for experiment 2&3	Zucker 1,6g	Zucker 44,6g
GDA label for experiment 2	Zucker 1,6g 2%	Zucker 44,6g 49%
GDA label for experiment 3	Zucker 1,6g	Zucker 44,6g

Figure S4. Sample labels from experiments 2 and 3 with reduced nutrition information, showing only the sugar component. Abbreviations: TL, traffic light; GDA, guideline daily amount. Translations: Zucker=sugar.

Results

We find that reduced nutrition information yields weaker effects, see Table S1. TL labels, compared to purely numeric GDA information, increase healthy choices, which is only significant in experiment 3 (model “Label”). In both experiments, we find that the drift rate for TL labels is less negative towards the unhealthy boundary; this is significant in experiment 3 only.

Table S1
Model "Label" and "Label + Liking" for experiment 2 and 3

	Experiment 2	Experiment 3
% healthy choices GDA (SD)	44.57 (16.74)	47.5 (19.3)
% healthy choices TL (SD)	46.28 (18.6)	50.5 (20.1)
Model "Label"		
Intercept	-0.24	-0.10
Main effect label	Z=0.74; p=0.46	Z=2.20, p=0.03
Estimate (SE[a]) label	0.06 (0.09)	0.14 (0.06)
Model "Label + Liking"		
Intercept	0.15	0.29
Main effect label	Z=1.29, p=0.20	Z=1.84, p=0.065
Main effect liking	Z=13.31, p<0.001	Z=13.76, p<0.001
Estimate (SE[a]) label	0.11 (0.09)	0.15 (0.08)
Estimate (SE[a]) liking	0.67 (0.05)	0.56 (0.04)
Drift diffusion model		
Mean drift rate GDA	-0.16	-0.20
Mean drift rate TL	-0.11	-0.12
Comparison of mean drift rate	t(42)=1.07, p>0.25	t(42)=2.07, p=0.045

Note. [a] Standard error of the estimate.