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Influence of Branding on Preference-Based Decision Making

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Abstract
Branding has become one of the most important determinants of consumer choices. Intriguingly, the psychological mechanisms of how branding influences decision making remain elusive. In the research reported here, we used a preference-based decision-making task and computational modeling to identify which internal components of processing are affected by branding. We found that a process of noisy temporal integration of subjective value information can model preference-based choices reliably and that branding biases are explained by changes in the rate of the integration process itself. This result suggests that branding information and subjective preference are integrated into a single source of evidence in the decision-making process, thereby altering choice behavior.

Keywords
branding, decision making, diffusion model, evidence accumulation, drift rate, bias, cognitive processes, preferences, response bias, judgment

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Imagine shopping for clothes in a big department store. Suddenly, you come across two items that you find, aesthetically, equally appealing, and before too long, you opt for the one from your favorite designer brand. More strikingly, when making everyday decisions, we often sacrifice some visual or functional appeal to purchase products from more preferred as opposed to less preferred brands. What is the mechanism through which branding introduces a bias in our decisions? Despite some evidence that certain brain regions (e.g., prefrontal cortex, striatum, midbrain, and hippocampus) might collectively encode cultural biases that influence preference-based judgments (Kenning & Plassmann, 2008; McClure et al., 2004; Plassmann, O'Doherty, Shiv, & Rangel, 2008; Schaefer, 2009; Schaefer & Rotte, 2010), the mechanistic details of how this information is used to influence decision making remain elusive.

In recent neuroimaging and modeling experiments, researchers have posited that value- and preference-based decisions are formed by a stochastic accumulation of *relative* evidence (i.e., the difference in evidence provided by each decision alternative) to a decision boundary (Basten, Biele, Heekeren, & Fiebach, 2010; FitzGerald, Seymour, & Dolan, 2009; Gluth, Rieskamp, & Buchel, 2012; Hare, Schultz, Camerer, O'Doherty, & Rangel, 2011; Krajbich, Armel, & Rangel, 2010; Milosavljevic, Malmaud, Huth, Koch, & Rangel, 2010; Philiastides, Biele, & Heekeren, 2010), an account consistent with the general framework of sequential-sampling models such as the diffusion model (Bogacz, 2007; Ratcliff, 1978; Ratcliff & McKoon, 2008; Ratcliff & Smith, 2004; Ratcliff & Tuerlinckx, 2002). The diffusion model decomposes behavioral data (choice and reaction time, RT, data) into internal components of processing that reflect the rate (or efficiency) of the accumulation process (drift rate), the amount of evidence required to make a decision (starting point and decision boundaries corresponding to the two alternatives), and the duration of nondecision processes (nondecision time), such as stimulus encoding and response production, along with the variance in each of the components of processing.

It currently is unknown whether changes in behavior resulting from branding biases can be modeled with a similar mechanism and, if so, which processing stages branding exerts an influence on. Specifically, it remains

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unclear whether branding alters early sensory representations, later decision-related processing, or a combination of both. To test the influence of branding on decision making, we fitted the diffusion model to data collected using a preference-based decision-making task in which participants were required to make decisions with and without branding information.

There are several possible ways branding could influence choice behavior. We hypothesized that branding's influences on top-down processes affecting sensory processing would be seen as changes in nondecision times. Alternatively, a possible influence of branding on the amount of evidence required to make a decision would translate into changes in the separation between the starting point of accumulation and the decision boundary. Such a finding would suggest that individuals processed the brand information prior to starting the decision process itself. Finally, a direct influence of branding on the decision process would be seen as changes in drift rate, which is an index of the quality of the evidence used for the decision. Observed changes in drift rate would suggest that brand information and the subjective preference for the choice alternatives are integrated into a single source of evidence during the decision process itself.

Method

Participants

Twenty right-handed female volunteers were recruited for this study (mean age = 18.6 years, range = 18–21 years). All had normal or corrected-to-normal vision and reported no history of neurological problems. Informed consent was obtained according to procedures approved by the local ethics committee of the University of Nottingham School of Psychology.

Stimuli

A set of 150 images of clothing items from high-street vendors (i.e., popular retail clothing stores) was obtained from the Web. Images were placed on a uniform gray background and were resized to 500 × 500 pixels. In addition, 24 images of high-street fashion-wear logos were obtained from the Web and were matched approximately for size (width: 150 pixels; height: 40–50 pixels).

Behavioral paradigm

Participants initially provided preference ratings for each of the 150 items of clothing, using scales that ranged from −3 (*really dislike*) to 3 (*really like*) in increments of 1. Each item was presented in the center of the screen without branding information along with a rating slider. Participants used the arrow keys on a keyboard to move the slider and submit a preference rating. Subsequently, they were instructed to rank-order a set of 24 brand logos on the basis of subjective preference (1 = most preferred, 24 = least preferred). On the basis of this rating, the logos were split into a more-preferred-brand group (ranks 1–10) and a less-preferred-brand group (ranks 15–24). The four logos in the middle of the scale (ranks 11–14) were removed to create a distance between the more preferred and less preferred brands. No time limits were imposed in these tasks.

For the main task, we asked participants to make binary choices between paired more-preferred-brand and less-preferred-brand items. The pairing of more-preferred-brand and less-preferred-brand items was done to generate a continuum of difference ratings for the paired items (more-preferred-brand rating minus less-preferred-brand rating). This difference rating served as a measure of task difficulty; that is, in the absence of any branding information, choices between pairs of items with high positive and high negative difference ratings would be considered easier, whereas those with difference ratings close to or equal to 0 (indecision point) would be considered more difficult. Given our rating scale for items (from −3 to 3), the difference ratings could range from −6 to 6 (for a total of 13 difference-rating conditions). We chose to use only the 7 conditions around the indecision point (i.e., values between −3 and 3) to ensure that we collected enough trials per condition for the modeling to be reliable while keeping the total duration of the experiment within reasonable limits. Specifically, we generated 350 unique pairings (50 trials per difference rating) for each of the labels-present and labels-absent blocks. To generate the list of stimulus pairs, individual (i.e., participant-specific) item and brand preference ratings were used.

It is important to note that we ran two blocks of trials—one in which the brand labels were presented along with the items (labels-present block) and one in which the labels were absent (labels-absent block; see Fig. S1 in the Supplemental Material available online). All participants completed both blocks of trials. For the labels-absent block, we substituted a placeholder for the original labels that read *BRAND* for both items, in an effort to equalize the overall perceptual load across blocks. Crucially, different clothing items were used for the two blocks to avoid priming effects. Item assignment to each of the two blocks was randomized across participants. The order of the labels-present and labels-absent blocks was also counterbalanced across participants to avoid ordering effects.

On each trial, participants were presented with a pair of items (to the right and left of a fixation cross) for a maximum of 1,750 ms and were instructed to make a response as soon as they had formed a decision. Participants indicated their choice by clicking either the right or the left button of a mouse (using their index or middle finger, respectively), corresponding to the position of the chosen item on the screen. Items were removed from the screen as soon as a choice was made, and their offset was followed by an interstimulus interval (fixation cross) whose length varied randomly from 1,250 to 1,750 ms across trials.

Behavioral-data analysis

For each participant, we computed the proportion of more-preferred-brand choices and mean RTs (averaged over both preferred-brand and less-preferred-brand choices) for each of the seven task-difficulty levels (i.e., difference ratings), separately for the labels-present and labels-absent blocks. We tested for significant effects in these behavioral measures using a 2 (labels present vs. labels absent) × 7 (task difficulty) repeated measures analysis of variance (ANOVA).

Diffusion-model fits

The diffusion model assumes that two-choice decisions are made by a noisy process that accumulates information over time from a starting point (z) toward one of two choice criteria or boundaries (here, corresponding to more-preferred-label and less-preferred-label choices, respectively) separated by distance a. When one of the boundaries is reached, a response is initiated. In the diffusion model, the evidence that drives the accumulation process, the drift rate (v), is derived from the representation of the stimulus, and drift rate varies across the conditions of the experiment (here, the difference ratings for paired items). The better the quality of the evidence, the larger the drift rate toward the appropriate decision boundary, and the faster and more accurate the response.

The components of processing outside the decision process, such as encoding and response output, are combined in the model in a single parameter, the nondecision parameter (T_{er}). Within-trial variability (noise) in the accumulation process results in processes with the same mean value of drift rate terminating at different times (producing RT distributions) and sometimes at the wrong boundary (producing errors). RTs and accuracy are naturally integrated by the diffusion model: RTs are determined by nondecision time plus the time it takes for accumulated evidence to reach one of the boundaries, and which boundary is reached determines which response is given. The model abstracts these components of processing from RT and accuracy data and thus separates the values of drift rate, nondecision processes, and boundary settings.

The values of drift rate, the boundaries, and the nondecision parameter all vary from trial to trial. This assumption is required if participants cannot accurately set the same values from trial to trial (e.g., Laming, 1968; Ratcliff, 1978). Across-trial variability in drift rate is assumed to be normally distributed with standard deviation η. Across-trial variability in the starting point (equivalent to across-trial variability in the boundary positions) is assumed to be uniformly distributed with range s_z, and across-trial variability in the nondecision component is assumed to be uniformly distributed with range s_t. The diffusion model was fit to the data separately for each participant.

To fit the diffusion model to the data (Ratcliff & Tuerlinckx, 2002), the values of all of the components of processing identified by the model were estimated simultaneously from the data. Choice and RT distributions were fit by using a chi-square method. Specifically, the proportions of responses between and outside the 0.1, 0.3, 0.5, 0.7, and 0.9 RT quantiles (i.e., six bins with .1, .2, .2, .2, .2, and .1 response proportions) for more-preferred-brand and less-preferred-brand choices were computed from the data and the model, and a simplex minimization routine was used to adjust parameter values until the proportions best matched each other—that is, until the chi-square value was minimized (see Ratcliff & Tuerlinckx, 2002, for more details). These chi-square values provided an index of goodness of fit.

The chi-square values of 30 out of the possible 40 conditions in our task (20 participants × 2 block types) were well below their corresponding critical value, $\chi^2(62, N = 338) = 81.63$, $p = .05$, which suggested a good overall fit to the data. The majority of the remaining 10 fits were only marginally higher than the critical value. On the whole, the quality of the fits was consistent with the quality of fits found in previous applications of the diffusion model to psychological data (Ratcliff, Thapar, Gomez, & McKoon, 2004).

In the fits presented here, all that varied across the labels-present and labels-absent blocks, as well as across task-difficulty levels (i.e., item difference ratings), was drift rate. As in the analysis of the behavioral data, we tested for significant differences in drift rate between the different task-difficulty levels and across labels-present and labels-absent blocks using a 2 × 7 repeated measures ANOVA. There was a marginally significant 27-ms difference in nondecision times (paired t test, $p = .07$) between the labels-present and labels-absent blocks (see Supplemental Discussion and Analysis in the Supplemental Material), but there were no differences across task-difficulty levels. The other model parameters did not differ between the labels-present and labels-absent blocks or across the different task-difficulty levels. Mean model parameter estimates, along with chi-square values, for the labels-present and labels-absent blocks are shown in Table S1 in the Supplemental Material.

We also fit the data with two additional models—the leaky competing accumulator model (Usher & McClelland, 2001) and the linear ballistic accumulator model (Brown & Heathcote, 2008). In these two models, as in the diffusion model, information is accumulated continuously over time, but both the leaky competing accumulator and linear ballistic accumulator models assume that the choice between more-preferred-brand and less-preferred-brand items is a race between two separate accumulators. Both of these models yielded results that were qualitatively identical to those of the diffusion model (see Supplemental Discussion and Analysis and Fig. S2 in the Supplemental Material), a pattern of results consistent with results presented in Ratcliff (2006).

Effects of individual brand preference

Even though our experiment was designed primarily to look at the influence of branding on decision making by comparing decisions made with and without brand labels, we also looked to exploit the variability in the ratings of logos to test for parametric effects of branding within the labels-present block. Specifically, we divided trials in the labels-present block into three groups on the basis of the difference between logo ratings for more preferred brands and logo ratings for less preferred brands while collapsing across the seven levels of item difference ratings. We refit the diffusion model to each of the three groups to obtain drift-rate estimates. To formally test for parametric effects on drift rate across the three groups, we computed a regression slope through the corresponding drift-rate values separately for each participant and tested whether the overall slope across participants was significantly different from 0 (using a *t* test).

Results

For the labels-absent block, participants made choices purely on the basis of subjective preferences for items, and both choices and RTs were symmetrical around the indecision point. Specifically, participants chose items from the more-preferred-brand group more frequently when their brand's logo rating was higher than that of items from the less-preferred-brand group and vice versa. At the indecision point, participants chose items from each group with similar frequency—main effect of difference rating: $F(6, 114) = 108.13$, $p < 1 \times 10^{-6}$ (see Fig. 1a for the proportions of more-preferred-brand choices). RTs increased with task difficulty, $F(6, 114) = 15.75$, $p < 1 \times 10^{-6}$, and remained symmetrical around the indecision point (see Fig. 1b for mean RTs).

In contrast, for the labels-present block, we found prominent branding biases. Overall, participants chose items in the more-preferred-brand group significantly more often in this block compared with the labels-absent block, $F(1, 19) = 27.79$, $p < 1 \times 10^{-4}$ (see Fig. 1a). Post hoc *t* tests revealed that this difference was significant (all *p*s < .05) for all but the highest positive difference-rating condition. Naturally, in this block of trials, label preference could either be congruent with the item assigned the higher rating (positive item difference ratings) or incongruent (negative item difference ratings). There was therefore a significant interaction between block type (labels present vs. labels absent) and the difference in item ratings, $F(6, 114) = 4.65$, $p < 1 \times 10^{-3}$ (see Fig. 1a), whereby branding bias became more pronounced as the incongruity between the item and brand preference became larger (i.e., as the subjective ratings increased in favor of the items from the less-preferred brand).

A similar interaction was present in the RT data, $F(6, 114) = 3.55$, $p = .003$ (see Fig. 1b): Participants slowed down when there was incongruity between item rating and branding preference (i.e., trials in which the item from the less preferred brand had a higher preference rating than did the item from the more preferred brand). Finally, there was a small overall increase in RTs in the labels-present block, $F(1, 19) = 4.86$, $p < .05$ (see Fig. 1b) that was likely due to additional time spent encoding the brand information (see Supplemental Discussion and Analysis in the Supplemental Material).

For the diffusion-model fits (see Fig. 2 for overall quality of the fits to the data), we found that drift rate varied with overall task difficulty, $F(6, 114) = 84.11$, $p < 1 \times 10^{-6}$ (see Fig. 1c for drift-rate estimates), a result consistent with previous reports (Krajbich et al., 2010; Milosavljevic et al., 2010). Most important, however, we found that branding biases between labels-present and labels-absent blocks were also explained primarily by differences in drift rate, $F(1, 19) = 27.03$, $p < 1 \times 10^{-4}$ (see Fig. 1c and Supplemental Discussion and Analysis in the Supplemental Material). Post hoc *t* tests revealed that these differences were significant (all *p*s < .05) for all but the highest positive difference-rating condition, a pattern of results consistent with that for choice behavior (see Fig. 1a). These findings provide strong evidence that branding affects the rate/efficiency of the accumulation process itself (Leite & Ratcliff, 2011). More specifically, although drift-rate estimates for the labels-absent block were symmetrical around the indecision point, drift-rate estimates for the labels-present block were biased toward more-preferred-brand choices. Moreover, this drift bias increased systematically with increasing conflict between subjective item and brand preference; that is, the interaction between labels-present blocks and labels-absent blocks was significant, $F(6, 114) = 4.62$, $p < 1 \times 10^{-3}$ (see Fig. 1c).

Finally, to test whether there were parametric effects of drift rate within the labels-present block, we divided trials into three groups on the basis of the difference

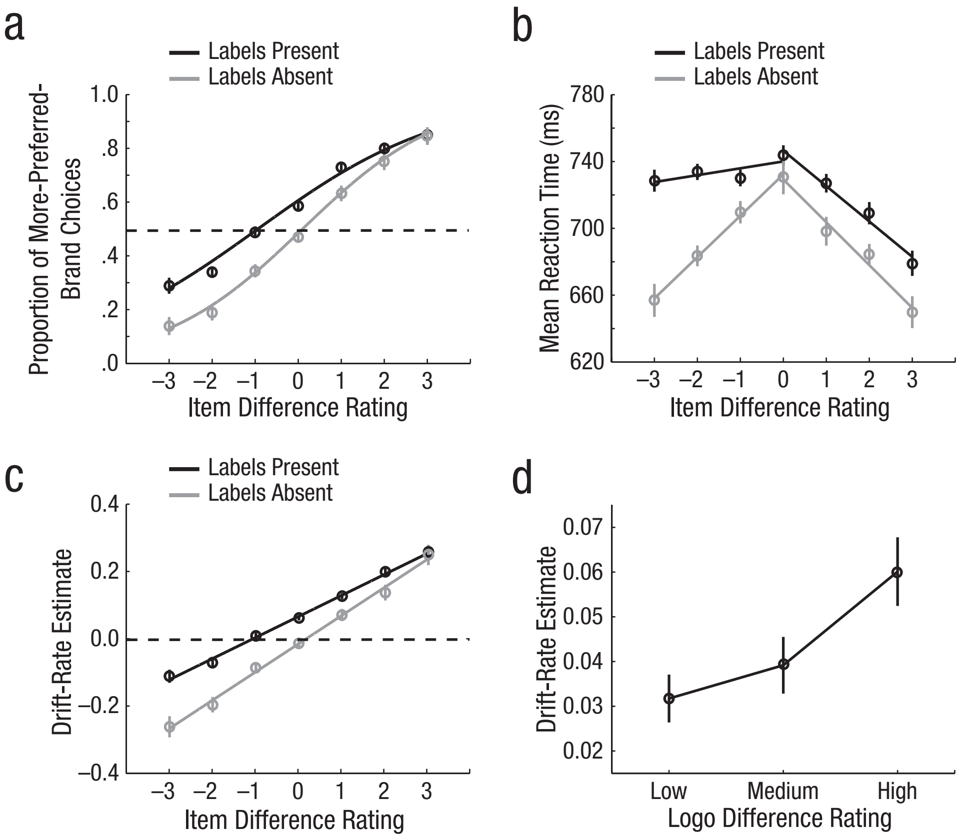

Fig. 1. Behavioral and modeling results. The (a) proportion of choices of more-preferred-brand items over less-preferred-brand items, (b) mean reaction times (averaged over both types of choices), and (c) drift-rate estimates from the diffusion model are plotted as a function of item difference rating and condition (labels present vs. labels absent). Drift-rate estimates are positive for more-preferred-brand choices and negative for less-preferred-brand choices. The zero point on the abscissa represents trials for which the item ratings for the more preferred and less preferred brands were equal (the most difficult trials). High positive values on the *y*-axis represent trials for which the item ratings were higher for the more-preferred-brand group than for the less-preferred-brand group, and high negative values represent trials for which the item ratings were higher for the less-preferred-brand group than for the more-preferred-brand group (easier trials). For drift-rate estimates for the leaky competing accumulator and linear ballistic accumulator models, see Figure S2 in the Supplemental Material. The graph in (d) presents drift-rate estimates as a function of logo difference ratings (i.e., the difference between ratings of logos for more preferred brands and ratings of logos for less preferred brands), collapsed across all difficulty levels. For this analysis, trials were divided into three groups (low-, medium-, and high-difference groups) on the basis of logo difference ratings. Fits are logistic in (a) and linear in (b) and (c). Error bars represent within-subjects (Cousineau, 2005) standard errors.

between more-preferred-brand and less-preferred-brand logo ratings (low-, medium-, and high-difference groups). We found that drift rates increased systematically as the difference between more-preferred-brand ratings and less-preferred-brand ratings increased, $t(19) = 2.54$, $p < .01$ (see Fig. 1d for drift-rate estimates). This finding suggests that branding biases existed not only across the labels-present and labels-absent blocks but also within the labels-present block itself, and therefore provides additional evidence that the observed choice biases were mediated by individual brand preferences.

Discussion

Our findings confirm that binary-value-based decisions involve a comparison process between items' values whereby the relative evidence (the difference in values) is accumulated over time to a decision boundary representing the selected item. These results are consistent with computational and neurobiological accounts already proposed for perceptual decision making (Gold & Shadlen, 2007; Heekeren, Marrett, & Ungerleider, 2008; Philiastides & Sajda, 2006b; Ratcliff, Philiastides, & Sajda,

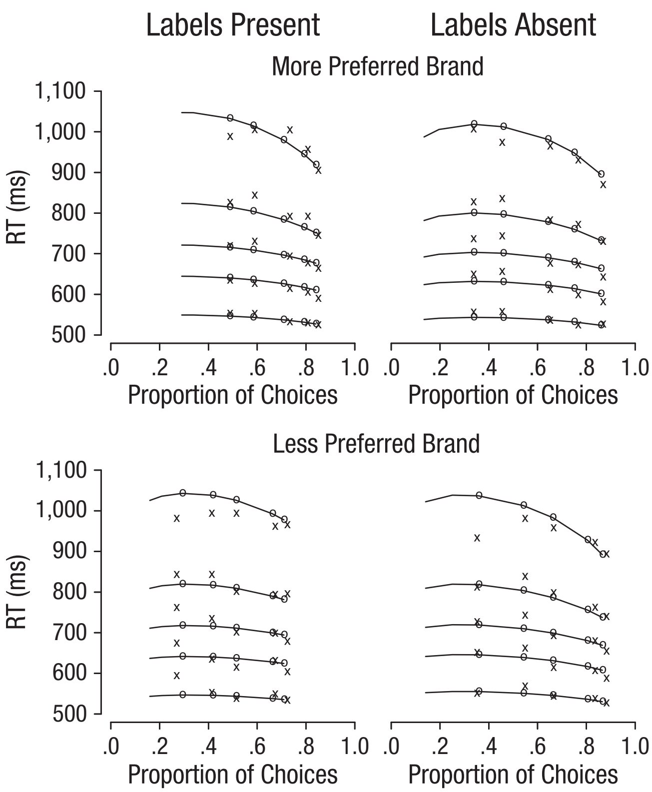

Fig. 2. Diffusion-model fits showing theoretical-diffusion-model (O) and empirical (X) quantile-probability plots for the labels-present and labels-absent blocks, separately for the more-preferred-brand and less-preferred-brand choices. The graphs show quantile reaction time (RT) as a function of the proportion of each type of choice. The RT quantiles, in order from bottom to top, are the .1, .3, .5, .7, and .9 quantiles. In each line, the data points correspond to the different difficulty levels (i.e., item difference ratings). Quantiles resulting from less-preferred-brand choices for a difference rating of 3 and more-preferred-brand choices for a difference rating of −3 are not shown because more than 1 participant had fewer than five responses, so average quantiles could not be computed across participants. In fitting for these conditions, a median split that produced two bins was used instead of the six bins produced from five quantiles.

2009; Shadlen & Newsome, 2001). Most important, however, our data offer strong support that branding information can influence this comparison process by introducing a drift bias toward more-preferred-brand items, likely by assigning greater weight to values of more-preferred-brand items, discounting values of less-preferred-brand items, or both. In turn, this drift bias leads to a choice bias for items assigned more-preferred-brand labels, with the most prominent bias effects arising when the item preference and brand preference are in conflict.

Although the diffusion model has been used to describe a large variety of psychophysical phenomena in research (McKoon & Ratcliff, 2012; Ratcliff, Gomez, & McKoon, 2004; Ratcliff & Starns, 2009; Ratcliff, Thapar, et al., 2004; Wenzlaff, Bauer, Maess, & Heekeren, 2011; White, Ratcliff, Vasey, & McKoon, 2010), including recent attempts to model value- and preference-based decisions (Krajbich et al., 2010; Milosavljevic, Koch, & Rangel, 2011; Milosavljevic et al., 2010), this is the first instance in which the model has been used to explore branding effects on consumer choices. Crucially, the novelty of our findings lies in the fact that unlike other forms of decision bias that are mediated through changes in the distance between the starting point of accumulation and decision threshold—such as biases due to changes in prior probability or potential payoffs associated with different alternatives (Leite & Ratcliff, 2011; Mulder, Wagenmakers, Ratcliff, Boekel, & Forstmann, 2012; Simen et al., 2009)—branding biases are explained exclusively by changes in drift rate. In other words, instead of baseline changes in activity of brain regions containing integrator neurons, branding alters the integration of value in the decision process itself. In a corresponding manner, branding does not appear to affect early sensory representations, given that changes in early sensory representations would have been manifested as changes in nondecision times across different levels of task difficulty (see Supplemental Discussion and Analysis in the Supplemental Material); it thus appears that branding does not alter the general aesthetic appeal of an item.

At the neural level, it seems logical that activity of brain regions that previously have been shown to encode similar biases (e.g., prefrontal cortex, striatum, and hippocampus; Kenning & Plassmann, 2008; McClure et al., 2004; Plassmann et al., 2008; Schaefer, 2009; Schaefer & Rotte, 2010) are likely to be involved in altering the subjective value representation of the various alternatives, thereby changing the relative amount of evidence used in the decision process. The relative deployment of attention between the alternatives (through visual-fixation patterns) might also contribute to the observed biases (Krajbich et al., 2010; Krajbich, Lu, Camerer, & Rangel, 2012). In turn, the ventromedial prefrontal and orbital frontal cortices, which recently have been shown to encode accumulated value information via a decision-comparator operation (Basten et al., 2010; FitzGerald et al., 2009; Gluth et al., 2012; Hare et al., 2011; Krajbich et al., 2010; Milosavljevic et al., 2010; Philiastides et al., 2010), are likely sites on which the influence of branding is expressed.

Intriguingly, our results may have major implications on characterizing the influence of branding on consumer choices and informing future marketing strategies and design of new neuromarketing tools. In everyday life, consumers are constantly required to make quick decisions about competing products. With advances in the technology of production, however, differentiating the intrinsic nature of rival products is becoming more and more difficult. As a result, branding has materialized as a substantial element of marketing strategies, and it appears to have developed into an important determinant of consumer choices (Anand & Shacchar, 2004; Ataman, Van Heerde, & Mela, 2010).

Our data confirm this view by offering mechanistic support to the notion that brand names are amalgamated with representational values during decision formation and, as such, are becoming the crux of product differentiation. This, in turn, suggests that it is not sufficient for companies to try to attract consumers with price promotions, good customer support, or product-specific technical requirements (e.g., updates). Instead, companies should place special emphasis on brand design and awareness and strive to promote strong affective associations with their brand among customers to develop and maintain a competitive advantage.

Moreover, with advances in marketing research, neuromarketing is emerging as an important element of optimizing product design and advertising. Current neuromarketing strategies focus on extracting neural signatures associated with processes such as attention, memory retention, and emotional engagement (Pradeep, 2010) and using them as metrics to tag various product attributes as more or less effective. Not only is isolating each of these processes difficult to accomplish, but consumer choices are ultimately based on the combined, internally weighted influence of these processes. Our findings endorse this interpretation and support a more straightforward implementation of such neuromarketing devices. Specifically, to infer product appeal more reliably, one instead needs to exploit a downstream signal that represents the aggregate representation of these influences—that is, the rate of integration in the decision process itself, which is a robust predictor of choice preference or bias, as we showed here, and can be measured reliably using noninvasive neuroimaging methods (Basten et al., 2010; Gluth et al., 2012; Philiastides, Ratcliff, & Sajda, 2006; Philiastides & Sajda, 2006a, 2006b; Ratcliff et al., 2009).

Finally, other cultural biases likely affect decision making through a mechanism similar to that of branding and should therefore be looked at in a similar light. In a corresponding manner, studying individuals who are potentially immune to such biases (e.g., experts in a field or product line; Harvey, Kirk, Denfield, & Montague, 2010; Kirk, Harvey, & Montague, 2011) should provide a better understanding of how these biases are mediated and controlled.

Author Contributions

M. G. Philiastides developed the study concept, designed the experiments, and collected the data. M. G. Philiastides and R. Ratcliff both analyzed and interpreted the data, wrote this article, and approved the final version of the article for submission.

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Declaration of Conflicting Interests

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

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Supplemental Material

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

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