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From “Where” to “What”: Distributed Representations of Brand Associations in the Human Brain

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Abstract

Considerable attention has been given to the notion that there exists a set of human-like characteristics associated with brands, referred to as brand personality. Here we combine newly available machine learning techniques with functional neuroimaging data to characterize the set of processes that give rise to these associations. We show that brand personality traits can be captured by the weighted activity across a widely distributed set of brain regions previously implicated in reasoning, imagery, and affective processing. That is, as opposed to being constructed via reflective processes, brand personality traits appear to exist a priori inside the minds of consumers, such that we were able to predict what brand a person is thinking about based solely on the relationship between brand personality associations and brain activity. These findings represent an important advance in the application of neuroscientific methods to consumer research, moving from work focused on cataloguing brain regions associated with marketing stimuli to testing and refining mental constructs central to theories of consumer behavior.

INTRODUCTION

Marketers have long appreciated the role of brand positioning, the location that a brand occupies in consumers’ minds relative to competing offerings, in guiding managerial decision making (Aaker 2009; Gardner and Levy 1955; Keller 1993). An understanding of how consumers feel and think about brands, for example, provides valuable guidance to developing marketing strategy in areas including advertising, pricing, and channel strategies. Moreover, as branding has grown to more and more focus on abstract and intangible considerations, marketers have increasingly sought to understand aspects of brand knowledge not related to the actual physical product or service specifications per se (Aaker 2012; Keller 2003).

In response, there has been a considerable effort by consumer researchers to decompose consumer response to brands into their component parts, e.g., feelings, imagery, likability (Alba and Hutchinson 1987; Bettman 1970; Keller 2003; Zaltman and Coulter 1995). This has resulted in a set of sophisticated typologies that provides rigorous scientific characterization to these complex perceptions. One canonical typology, for example,

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involves the characterization of the widely held notion that consumers endow brands with a set of human-like characteristics akin to personality (Aaker 1997; Levy 1959). The resulting brand personality framework, as proposed in the seminal work by Aaker (1997), uncovered five basic dimensions that together provide a highly robust and general account of the perceptual space underlying brands.

Despite these successes, research in consumer psychology has been largely silent on the specific processes by which intangible characteristics such as brand personality are generated and organized (Johar, Sengupta, and Aaker 2005; Keller and Lehmann 2003). More broadly, because mental constructs such as brand personality have traditionally only been measured by self-report methods, it remains challenging for researchers to probe such knowledge in cases where consumers are unable or unwilling to fully articulate their thoughts and preferences (Ariely and Berns 2010; Haire 1950; Zaltman and Coulter 1995). Such insights are central to efforts by marketers to understand and predict the extent to which marketing actions can successfully create or affect these thoughts and feelings, which in turn influence consumer response to marketing activities (Batra, Lenk, and Wedel 2010; van der Lans, Van den Bergh, and Dieleman 2014).

Emerging techniques in neuroscience, therefore, have been widely viewed as having the potential to overcoming limitations of self-report measures by directly accessing mental contents on part of the consumers (Ariely and Berns 2010; Plassmann, Ramsøy, and Milosavljevic 2012; Yoon et al. 2012). Perhaps most excitingly, by capturing the entire decision-making process, modern functional neuroimaging techniques have the promise to elucidate the multitude of processes engaged during consumer choice, such that the effects of marketing actions on such processes could be traced, compared, and valued.

In the context of branding, an important open question concerns the extent to which there exists a stable “mental map” of brand knowledge from which brand personality associations emerge (Keller 2003; Zaltman 1997). This is important for two reasons. First, the assumption of a stable store of knowledge underlies all existing research efforts using self-report measures to probe the intangible characteristics consumers associate with brands. Substantial research exist, however, suggesting that recall is often not equivalent to retrieval of information in memory but may be the construction of a plausible response (Johar, Maheswaran, and Peracchio 2006). In the extreme case, participant responses may be constructed to suit the explicit questions of consumer researchers, and that these explicit measures have little to do with actual thoughts that participants have about the brands. That is, it is unclear whether intangible characteristics such as brand personality traits exist “a priori” in the minds of the consumers, or whether they are a product of reflective process, such that they are influenced by experimenter elicitation. Second, the existence of such a map opens the door for neuroscientific methods to address a number of additional important questions, such as how consumers’ mental representations of brand personality are affected by marketing actions, and what are the different cognitive processes that act on these representations.

Although of course still preliminary and incomplete, existing studies using functional neuroimaging techniques have already made important inroads in addressing some of these processes. For example, it has provided evidence for inferences about the role of emotional processing in decoy effects on the basis of amygdala activation (Hedgcock and Rao 2009), where the introduction of a third normatively irrelevant alternative was associated with significantly lower activation in areas of the brain associated with negative emotion.

“What?” versus “Where?”

Despite these advances, there remain important conceptual and methodological hurdles that arise from fundamental differences between the typical goals and questions in neuroscience and marketing. In particular, localization approaches in cognitive neuroscience by their nature are focused on “where”-type questions (Churchland and Sejnowski 1988; Gazzaniga 2004). For example, where in the brain does overall activation between animate and inanimate objects differ (Kriegeskorte et al. 2008)? Does the hippocampus engage more vigorously during episodic memory retrieval versus encoding (Schacter and Wagner 1999)?

Answering such “where”-type questions have been invaluable in understanding how the brain organizes basic cognitive processes and how they relate to more complex constructs and representations. The fact that altruistic punishment engages brain regions known to respond to basic rewards provided early evidence that altruistic punishment may also be rewarding at a basic neurobiological level (de Quervain et al. 2004). In the context of brand personality, the pioneering study of Yoon et al. (2006) found important differences in processes at the neural level that are associated with trait judgments about brands and people. Specifically, compared to judgment of human traits, judgment of brand traits elicited greater engagement of inferior prefrontal cortex, an area known to be involved in object processing, thereby challenging a strictly anthropomorphic view of brand personality.

For many if not most consumer researchers, however, these “where”-type questions are secondary to understanding the contents and processes that reside within the brain. That is, consumer researchers, in contrast to neuroscientists, are typically interested in “what”-type questions. For example, what are the set of associations that goes through the mind of consumers when they are presented with a particular brand? How are these associations affected by marketing actions?

Despite the intuitive nature of such question, it has not been one that previous neuroimaging studies have been equipped to address. Specifically, whereas neuroscience has generally been able to deliver “where” answers, marketing continues to ask “what” questions. Marketers want to know “what is going through consumers’ minds when looking at a Coca-Cola advertisement?”, but neuroscience has traditionally delivered “the value of Coca-Cola can be detected in regions such as the ventromedial prefrontal cortex”.

In particular, localization approaches may fail to capture representations and processes that are not contained in any single set of brain regions, but rather emerge from the correlated activity across a network of brain areas (Kriegeskorte, Goebel, and Bandettini 2006; Mitchell et al. 2008). That complex constructs such as conceptual knowledge emerge out of a distributed system has a long and distinguished history dating back at least to Lashley’s search for engrams (Lashley 1950) and connectionist models of learning systems (Hinton, McClelland, and Rumelhart 1986; McClelland and Rogers 2003).

At the extreme, an inability to address "what"-type questions leaves open the possibility that brain regions thought to underlie a specific process is actually involved in some completely unrelated process. For example, amygdala activation in the decoy effects may instead be related to some other aspect of the task that has nothing to do with decoy effects (Huettel et al. 2009; Poldrack 2011). This is particularly salient in the case of consumer neuroscience given the complexity of marketing stimuli. One way to address this concern is to show that the information content in question is actually contained within the set of identified brain regions.

Connecting "What" and "Where"

Here we take an important step toward enabling consumer researchers to address both "what" and "where"-types of questions using brain imaging data (Kay et al. 2008; Kriegeskorte, Goebel, and Bandettini 2006; Mitchell et al. 2008). In more basic cognitive processes such as vision and memory, these methods have revolutionized the abilities of researchers to ask questions about how information is encoded, maintained, or retrieved at various stages of processing in ways that test and inform psychological theories of memory and perception (Kay et al. 2008; Rissman and Wagner 2012). The central insight of this approach is to use cross-validation techniques to consider whether a distributed set or "pattern" of brain activity contains some set of information predicted by cognitive and behavioral theories (Kriegeskorte, Goebel, and Bandettini 2006; Poldrack 2011).

First, to address the "what" question, we attempt to recover the set of thoughts and feelings that consumers associate with brands in a passive viewing task. Importantly, the participant in our experiment is not prompted to make any specific judgment, but rather is asked to freely think about the brand. If brand personality traits associated with brands exist in the mind of the consumer a priori, we should in principle be able to "read out" these contents based on brain activity alone. On the other hand, this would not be possible if traits were solely the consequence of ratings prompted on the part of the researcher.

This approach is based on two key assumptions. First, we assume that mental representation to brand personality is contained in the responses of a stable and possibly distributed network of regions (Kriegeskorte, Goebel, and Bandettini 2006; Mitchell et al. 2008). That is, there exists a stable mapping between brain and mind such that mental representation of brand personality is reflected in the activity levels of a network of brain regions. Second, we assume that the psychological architecture provides a reasonable first-order approximation of the mental representation (Mitchell et al. 2008; Poldrack 2011). In the case of brand personality, this is equivalent to assuming that each brand is located within a 5-dimensional representation space (captured by Sincerity, Competence, etc.), where the specific location is given as a 5-tuple within the space.

> **Assumption 1:** There exists a neural representation, consisting of possible a widely distributed network, of mental representation of brand personality.
>
> **Assumption 2:** The brand personality framework captures mental representations of a set of intangible brand characteristics.

Importantly, our second assumption makes clear the distinction between our approach and those of previous studies aimed at predicting consumer choice (Deppe et al. 2005; van der Laan et al. 2012; Murawski et al. 2012; Tusche, Bode, and Haynes 2010). In this latter set of studies, decoding was conducted based on observable choice behavior, and no attempt was made to test the plausibility of models of the underlying psychological processes. In the same way that early decoding studies of visual systems (e.g., Haxby et al. 2001; Haynes and Rees 2005) were conducted with no reference to the intermediate psychological features underlying observable *inputs* (for example, faces, houses), these studies make no references to intermediate psychological processes underlying observable *outputs*. In contrast, our approach is referred to as model-based decoding, which distinguishes from those that do not assume some underlying model of the representational space (for details, see Haynes and Rees 2006; Poldrack 2011).

More specifically, by identifying the particular brand a person is thinking about based the evoked brain responses, our study requires brand personality framework to offer greater predictive power compared to null models that do not capture these characteristics. That is, based on how a person’s brain differentially responds to Coca-Cola and Pepsi, we ask whether it is possible to learn about the representational space of brand personality in the brain, and use this relationship to infer whether that person is thinking about Apple or Microsoft.

> **H1:** Brand personality traits associated with brands exist in the mind of the consumer a priori, and can be recovered from brain activity during a passive viewing task.

Next, to connect “what” to “where”, we will characterize the set of brain regions that contain brand personality information. This enables us to address the extent to which brand personality contents are distributed in the brain. In previous decoding studies, contents related to more basic perceptual processes have been found to be contained in relatively circumscribed regions of the occipital and temporal lobes (Kriegeskorte et al. 2008; Naselaris et al. 2009). This is the case even for relatively abstract constructs such as objects and faces, which are largely restricted to regions within the inferior temporal cortex, or biological motion in the superior temporal sulcus (Haynes and Rees 2005; Kriegeskorte et al. 2008). In contrast, higher-order constructs such as conceptual knowledge have been shown to have a much more distributed neural basis, drawing upon a wide set of brain regions, including those involved in sensory processing as well as higher-order cognitive regions (Mitchell et al. 2008; Tyler and Moss 2001).

More importantly, the resulting map of predictive regions will allow us to make inferences about the processes by which brand personality emerges. Previous neuroimaging studies have implicated a diverse array of brain regions in brand processing, including regions involved in autobiographical memory and person judgment (MPFC, Deppe et al. 2005; Schaefer and Rotte 2010; Schaefer et al. 2006), semantic memory retrieval (LPFC, Klucharev, Smidts, and Fernández 2008; McClure et al. 2004; Yoon et al. 2006), affective processing and interoception (insula, Bruce et al. 2013), episodic and spatial memory (hippocampus, Esch et al. 2012; McClure et al. 2004), among others. Although these findings are typically discussed in isolation, it is possible that they all reflect a shared set of cognitive and affective processes from which brand personality representation emerges.

> **H2:** Consistent with connectionist models of learning and memory, brand personality contents are distributed widely across the brain.

METHODS

Participants

A total of 17 participants (6 females, mean age 34.2, S.D. 6.5) from the San Francisco Bay Area were recruited from Craigslist to participate in the functional magnetic resonance imaging (fMRI) study. Although this is on the lower end of standard functional neuroimaging studies based on univariate approaches, it is on par with or exceeds those of comparable multivariate decoding studies (Formisano et al. 2008; Mitchell et al. 2008). The total time for the whole experiment was approximately 3 hours, including the instruction, the scanning session, and the post-experiment questionnaires. Each participant was paid $70 in cash upon completion of the experiment. A further 25 undergraduate students were recruited for a behavioral-only study in exchange for course credits. These participants completed an online questionnaire on the same set of brands and traits of the brand association scale. All informed consent was obtained as approved by the Internal Review Board at University of California, Berkeley.

Procedure

Participants in the fMRI study underwent scanning in a passive viewing task involving logos of 44 well-known brands (Figure 1A). The set of brands were selected from the list of 100 Best Global Brands (Interbrand, available at: www.interbrand.com) to ensure diversity in brand associations and represented industries. Each of the 44 stimulus items was presented four times in a pseudo-random sequence on the gray background (Figure 1B), and each presentation lasted for 4-8s. Participants were instructed prior to the scanning session to think about the characteristics or traits associated with the brand, but that they were free to think about any characteristic or trait such that no attempt was made to obtain consistency of the associations neither across participants nor across repetition times. Following scanning, participants completed a survey including the 42-item brand association scale (Aaker 1997), familiarity, and preference for each of the 44 brands. The brand association scale involved judgment of the descriptiveness of 42 traits to each brand (Table S1, see *Web Appendix*), with a five-point scale from not at all descriptive (rating=1) to extremely descriptive (rating=5).

fMRI Data Acquisition

Functional images were acquired on a Siemens 3T TIM/Trio scanner at Henry H. Wheeler Jr. Brain Imaging Center at University of California, Berkeley. An EPI sequence was used to acquire the functional data: repetition time (TR) = 2,000ms; echo time (TE) = 30ms; voxel resolution = 3mm × 3mm × 3mm; FOV read = 192mm; FOV phase = 100%; interleaved series order. The scan sequences were axial slices approximately flipped 30 degrees to the

AC-PC axis. High-resolution structural T1-weighted scans (1mm × 1mm × 1mm) were acquired by using an MPRage sequence.

Behavioral Data Analysis

To characterize personality features associated with our brands using participant ratings on the set of traits outlined in the Aaker framework (Figure 1C), we used a factor analytic approach to summarize variation in trait ratings and reduce collinearity issues (Aaker 1997). Mean trait ratings were factor-analyzed using principal components analysis and varimax rotation. Factors were selected if the associated eigenvalue were greater than one and explained a significant portion of variance (Table S2, see *Web Appendix*). Each brand was re-expressed in terms of its personality vector, defined as the strength of association between the brand and the personality factors, such as Excitement and Competence.

fMRI Data Preprocessing

Image data were preprocessed in the following order using SPM8 (Statistical Parametric Mapping, Wellcome Trust Centre for Neuroimaging): correction for slice time artifacts, realignment, coregistration to the subject's T1 image, normalization to Montreal Neurological Institute coordinates. Finally, consistent with previous MVPA studies, data were left unsmoothed to preserve local voxel information (Clithero, Carter, and Huettel 2009; Haynes and Rees 2006).

fMRI Data Analysis

An illustration of our analytical approach is presented in Figure 2. Below we summarize briefly the main analytical process before describing the steps in more detail. Following extraction of a representative fMRI image for each brand, we will hold-out two brands out of the set of 44 total brands, e.g., Disney and Gucci (Figure 2A). These brain responses, together with the brand personality factors for the 42 remaining in-sample brands (Figure 2B), are used to obtain an fMRI map for each of the five brand personality factors (Figure 2C). This enables us to calculate predicted fMRI maps for each of the two hold-out fMRI image for Disney and Gucci by combining the brand personality factor scores of the hold-out brands with the brand personality fMRI maps (Figure 2D). Finally, we ask whether we are able to correctly predict whether each hold-out brand is Disney or Gucci by comparing the similarity between the predicted and actual neural maps. Once completed, this procedure is then iterated over all possible pairwise combination of brands, and significance testing is performed using a permutation procedure by shuffling over the fMRI image and brand personality pairings. Below we provide more detailed description of the procedures:

1. Extracting neural responses to brands—To identify the representative fMRI image of a brand, we used the procedure outlined in Mumford et al. (2012) to account for the fact that in rapid event-related designs the evoked BOLD signal for adjacent trials will overlap in time. We first used a general linear model in SPM8 to estimate a single fMRI image for each of the 176 brand presentations using method LS-S in Mumford et al. (2012), where each event was modeled as an impulse function convolved with a double gamma hemodynamic function. The beta values estimated for the first regressor of the brand of interest were used as the brain activation patterns associated with a brand at a particular repetition time (see *Web Appendix* for robustness checks using alternative methods of estimating representative fMRI images).

Using brain images for each brand at each repetition time, we standardized the activation levels for each voxel by z-scoring over the 176 files. Then, for each brand, we averaged the four brain images of the four repetition times to obtain the averaged fMRI image associated with thinking about the brand. Finally, we applied the individual grey matter mask to include voxels within the grey matter.

2. In-sample model training—To infer the engagement of specific mental representations from pattern of neural responses, we took a model-based approach in which the decoding of brain activation patterns is guided by quantitative models capturing psychological features underlying specific mental representations (Mitchell et al. 2008; Naselaris et al. 2011; Poldrack 2011). The underlying hypothesis of our approach is that neural representation of consumer brands is related to the strength of association of an individual brand to its personality features. That is, we assume that neural response y_j^v in voxel v to brand j is given by:

$$y_j^v \quad = \quad c_1^v f_{1,j} + c_2^v f_{2,j} + \cdots + c_n^v f_{n,j} \qquad \text{(Equation 1)}$$

where $f_{n,j}$ is the value of the nth personality feature for brand *j*, and c_n^v is a scalar parameter that specifies the degree to which the nth feature activates voxel *v*. More specifically, c_n^v defines the relationship between the brain activation level and the brand personality features.

Model-based decoding was performed using a cross validation approach in which the model was repeatedly trained using 42 of the 44 available stimulus brands, then tested using the two hold out stimulus brands. We denote the neural response y_j^v in voxel v to brand j as $y_j^v \quad = \quad c_1^v f_{1,j} + c_2^v f_{2,j} + \cdots + c_n^v f_{n,j}$ (Equation 1). We trained the model on each iteration using the set of observed fMRI images associated with 42 known brands, to obtain c_n^v values via maximum likelihood. More specifically, we reconstruct the relationship between the brain activation level (as dependent variables) and the brand personality features (as independent variables) with the multiple regression approach, using only 42 of the 44 available stimulus brands. We then test the model performance on the two hold-out brands, which are not in the training set.

3. Model prediction using hold-out sample—Once trained, the model was tested by presenting the fMRI images (i_1 and i_2) associated with two hold out brands (b_1 and b_2). This consisted of comparing (i_1 and i_2) with the two predicted fMRI images (p_1 and p_2) associated with two hold out brands, where (p_1 and p_2) were computed using weights c_n^v and the set of personality features $\{f_{1,k} \ldots f_{n,k}\}$ for the two hold out brands. For example, in an iteration where Disney and Gucci were excluded from the training, we reconstructed the relationship between the brain activation level and the brand personality features using other 42 brands with Equation 1. Then, using Disney's personality factor scores, we can calculate the predicted activation level for each voxel using Equation 1 and the learned c_n^v values, with those we can create the predicted brain image for Disney. We call the model-predicted brain images p_1 and p_2, and the observed brain images i_1 and i_2, for the two hold-out brands.

To evaluate the performance of the model, the model is required to correctly match (i_1 and i_2) to (b_1 and b_2) using (p_1 and p_2), as assessed by which match had a higher correlation value. More specifically, let sel(i) be the vector of values of the selected subset of voxels for image i. The similarity score between a predicted image, p, and observed image, i, was calculated as the Pearson correlation coefficient of the vectors sel(p) and sel(i) . It then decided which was a better match: ($p_1=i_1$ and $p_2=i_2$) or ($p_1=i_2$ and $p_2=i_1$), by choosing the image pairing with the larger sum of similarity scores. The expected accuracy in matching the two left-out brands to their left-out fMRI images is 0.50 if the matching is performed at chance levels.

As described above, similarity between two images was calculated using only a subset of the image voxels, following methods proposed in Mitchell et al. (2008). Voxels were selected automatically during training, using only the 42 training brands on each of the leave-two-out cross validation folds. To select voxels, all voxels were first assigned a stability score using the data from the 4 presentations of each of the 42 training stimuli. Given these 4*42 = 168 presentations (168 fMRI images), each voxel was assigned a 4×42 matrix, where the entry at row i, column j, is the value of this voxel during the i^{th} presentation of the j^{th} brand. The stability score for this voxel was then computed as the average pairwise correlation over all pairs of rows in this matrix. In essence, this assigns highest scores to voxels that exhibit a consistent (across different presentations) variation in activity across the 42 training stimuli (see *Web Appendix* for details).

4. Significance testing—To calculate statistical significance, we used a permutation procedure to empirically estimate the null distribution (Mitchell et al. 2008). Specifically, a null model was estimated on each iteration by shuffling the fMRI image and brand personality pairing. For example, on a particular iteration, as opposed to using the true brand personality score, we may use Google’s personality features to describe Gucci, or IBM to describe Campbell’s. Under the null hypothesis that the brand personality framework provides no information about the underlying neural representation, these shuffled brain-brand pairings should yield prediction rates similar to the actual pairings. The null distribution is then calculated using the pooled 600 permuted models from each of the 17 participants, for 10,200 models in total.

BEHAVIORAL RESULTS

Brand Personality Factor Structure

First, we sought to characterize the set of personality feature $f_{n,j}$ associated with our brands using participant ratings of brands on the set of traits outlined in the Aaker framework (Figure 1C, Table S1 in *Web Appendix*). Specifically, we used a factor analytic approach to summarize variation in trait ratings and reduce collinearity issues. Consistent with previous results, we found that a substantial proportion (86%) of the variance was captured by 5 factors (Table S2 in *Web Appendix*). Further inspection of the factor loadings showed that our results largely replicated those of previous studies (Figure S2 in *Web Appendix*) (Aaker

1997). For example, the first factor loaded highly on the traits "trendy", "unique", and "cool"—commonly referred to as the Excitement factor. The third factor, referred as Sincerity, loaded highly on traits such as "friendly", "family-oriented", and "down-to-earth". Using this factor analytic framework, therefore, it is possible to characterize each brand, for example, Apple, as a vector of personality features consisting of these five factors that summarizes the set of characteristics participants associate with these brands (Figure 1D, S3; Table S3 in *Web Appendix*).

Importantly, this association architecture allows us to account for some of the salient similarities and differences between brands apart from their product categories. For example, although Apple and Microsoft reside in the same industry, they elicit highly distinctive associations and are distinguishable in this association architecture (Figure 1D). In contrast, Disney and Ikea are similar in this framework despite differences in objective features (Figure 1D). Although this framework by no means captures all characteristics consumers associate with brands, it has been invaluable to researchers by capturing and organizing our knowledge in a parsimonious and tractable manner (Aaker 1997).

Robustness of Association Architecture

Furthermore, to investigate the robustness of our framework, as well as the degree to which these trait associations could be generalized to samples from different populations, we surveyed an additional sample of 25 undergraduate students on the same set of traits and brands. We found that the average responses of the trait scores were highly correlated among our neuroimaging subjects and the follow-up undergraduate participants (Pearson r=0.86, $p<10^{-10}$, Figure 1E), such that there was considerable agreement between the two samples regarding these brands despite different demographic and socioeconomic characteristics. These results show that this brand personality architecture enjoys considerable robustness across samples from different populations, suggesting its utility in organizing the underlying psychological associations.

NEUROIMAGING RESULTS

Brand Personality Traits Can Be Recovered From Brain Activity

Using results from the Aaker model, we next sought to relate personality factor scores with observed fMRI data associated with viewing brands using a cross-validation approach, and test the ability of our framework to discriminate between the previously unseen brands. For each iteration, two brands were held out of the training set, e.g., Disney and Gucci, and the model was trained using the remaining 42 brands (Figure 2A). Specifically, training involved regressing activation level of each voxel on the set of personality features of the training brands obtained from the factor analysis (Figure 2B). The derived maximum likelihood estimates were used as c_n^v terms, which were then combined with the personality factor scores of each hold-out brand to form its a predicted fMRI image. This leave-two-out train-test procedure was iterated 946 times, leaving out each of the possible brand pairs. (Figure 2C).

Following training, the computational model was evaluated by comparing these predicted fMRI images to the observed fMRI data of the two hold-out brands, evaluated over the 500 image voxels with the most stable responses across training presentations (Figure 2D). Specifically, given the two hold-out brands b_1 and b_2, we calculated their respective predicted images p_1 and p_2 using the set of personality feature $f_{n,j}$ associated with the hold-out brands and the set of weights c_n^v obtained from the training set. Next, using the actual fMRI images i_1 and i_2 associated with the two holdout brands, we asked whether the model was able to correctly match i_1 to p_1 and i_2 to p_2 by choosing the image pairing (i_1 v. p_1 and i_2 v. p_2) that is more highly correlated (Figure 2, for details see Web Appendix).

Under the null hypothesis of no association, the predicted fMRI image for a brand will be equally predictive of the matched brand as with the unmatched brand. In contrast, we found that the overall hit rate for iterating over all of the possible combination of holdout data was 58%, and highly significant as assessed using permutation test obtained by independently training 10,200 single-participant models with randomly shuffled personality features of brands ($p<10^{-5}$, see *Web Appendix*). These results are thus consistent with our hypothesis that brand personality exists in the mind of the consumer a priori (H1).

Furthermore, we found that the predictive power was strongly modulated by the psychological similarity of brands as measured by correlation of trait ratings. Separating the brand pairs based on psychological similarity into quartiles, we found that performance in classification substantially better when brands are dissimilar, where the averaged hit rate is 63% ($p<10^{-7}$). In contrast, predictive accuracy was not significantly different from chance when brands are highly similar (Figure 3A). This modulation of prediction rate by psychological similarity thus argues against the likelihood that our results were driven by some unrelated factors. Moreover, the fact that we were unable to distinguish neural responses to brands when their personality features are sufficiently similar can be interpreted as a boundary condition where the brain data no longer contains sufficient resolution to distinguish between brand personality representations.

Finally, these results were robust to a number of variations in specific analytical process, including method of extracting representative fMRI response to the brands (Figure S7), similarity metric (Figure S8), voxel selection (Figure S9-S10), excluding visual cortex voxels via masking (Figure S11), and controlling for physical properties of brand logos (Figure S12, see Web Appendix for details).

Neural Similarity Of Brands Is Modulated By Psychological Similarity

To more systematically examine the relationship between the psychological organization of brands and the discriminability of the associated brain images, we compared, for each brand pair, the correlation between predicted and observed brain images, evaluated over the 500 image voxels with the most stable responses across training presentations, against psychological similarity in brand meaning as measured by correlation of trait ratings (Figure 3B). We found that strength of neural correlation is robustly modulated by the similarity of brands' psychological properties (Pearson $r=0.56, p<10^{-7}$), such that brands that are more similar at the psychological level were also more highly correlated at the neural level (Figure 3B). For example, H&M and MTV are highly similar in their psychological associations as measured using a correlation index (Pearson r=0.78), whereas those for Disney and Gucci are highly distinct (Pearson r=0.17) (Figure S3, Table S3). Consistent with this pattern, neural signatures associated with H&M are more similar to those associated with MTV than Disney with Gucci (Pearson r=0.36 versus r=−0.27, respectively). Similar results were obtained using Euclidean distance as a measure of similarity (Figure S7, see *Web Appendix*). These results underscore the notion that the brand personality framework provides a reasonable first-order approximation of the mental representation, consistent with our Assumption 2.

Brand Personality Contents Are Distributed Widely Across The Brain

Having assessed the predictive validity of our decoding framework, we sought to characterize the set of brain regions where predicted neural response for held-out brands best correlated with the observed responses. To do so, we calculated the correlation coefficient of the predicted and observed fMRI response at each voxel location, and selected the set of regions where brain activity was significantly correlated with model predictions (see *Web Appendix*). Consistent with connectionist models of distributed representation (H2), we found that the set of predictive voxels were distributed throughout the brain (Figure 4, S6, S13-S17; Table 1). In contrast, these regions are not visible using a standard univariate GLM approach that ignores information contained in the spatially distributed set of brain regions (Figure S18).

To understand the cognitive functions in which these regions were most involved, we conducted an exploratory reverse inference analysis using NeuroSynth (Yarkoni et al. 2011), correlating our activation map with the neural activation maps for each term in the NeuroSynth database (Figure 4). We found that our activations were distributed across a number of types of cognitive functions, but in particular those implicated in previous studies of semantic knowledge (inferior frontal gyrus), imagery (premotor and visual cortex), and emotional processing (anterior and posterior cingulate gyrus), consistent with the notion that brand knowledge consists of a complex mix of thoughts, images, and feelings that consumers associate with brands.

DISCUSSION

The application of neuroscientific methods to marketing has a history that is brief in existence but long on controversy (Ariely and Berns 2010; Plassmann, Ramsøy, and Milosavljevic 2012). In a particularly high-profile incident, the New York Times published an op-ed titled “You Love Your iPhone, Literally”, by the brand consultant Martin Lindstrom (Lindstrom 2011), which prompted a group of 44 neuroscientists to co-sign a response letter condemning the article. Whatever the scientific merits of the claims, and indeed the data have never appeared in a peer-reviewed format, at the heart of the study lies a set of questions of great interest to marketers, consumer researchers, and the lay public alike. Namely, what are the set of thoughts and feelings that occur when people think or interact with the products that they own or are considering purchasing?

Here we take an important step toward bridging this gap, and begin to provide a neuroscientific framework to address these questions. More specifically, using a decoding approach in conjunction with factor analytic techniques, we formally test our ability of infer mental representations of brands using a set of intermediate psychological features to model the underlying representational space (Haynes and Rees 2006; Mitchell et al. 2008; Norman et al. 2006). In comparison to “where”-type questions that are the focus of traditional localization approaches, these “what”-type questions have only become addressable in recent years (Haynes and Rees 2006; Mitchell et al. 2008; Norman et al. 2006), and to our knowledge has not been attempted in consumer neuroscience.

First, consistent with our hypothesis that brand personality traits exist a priori inside the mind of the consumer (H1), we found that we were able to predict what brand consumers were thinking about solely based on the relationship between brand personality and brain activity. In particular, because participants in our study were not prompted on traits such as “daring”, “reliable”, and “wholesome” until after the scanning session, our likelihood of predicting what brands participants are thinking of should be at chance if such associations did not come across the consumers’ thoughts. In contrast, past studies have typically elicited subjective ratings online during scanning (Schaefer and Rotte 2010; Schaefer et al. 2006; Yoon et al. 2006), thereby leaving open the possibility that brand-related processing was at least in part induced by the specific stimuli used during the experiment.

Moreover, although the reported predictive accuracy was lower than rates observed in more basic perceptual domains (Haxby et al. 2001; Kay et al. 2008), they are comparable to those observed in previous studies of higher level cognitive processes, including those involving consumer choice (Knutson et al. 2007; van der Laan et al. 2012). Some of this may be attributable to our decision to not include fixation screen after every brand logo presentation. This was chosen based on reports from pilot participants that they found the number of fixation screens between brands to interfere with their ability to process brand traits, but this may have resulted in reduced efficiency in extraction of the representative brand fMRI image. Future studies would be needed to address the extent to which predictive accuracy can be improved.

Second, we found that neural responses to consumer brands can be decomposed into a basis set of neural activation patterns associated with intangible characteristics of these objects, and that these results were robust to a number of variations in the specific analytical process (see Supplementary Results and Figures S7-S12 in *Web Appendix*). Moreover, our findings are consistent with connectionist models of conceptual knowledge where brand personality associations emerges from weighted activity across a distributed set of units (H2) (Binder et al. 2009; Tyler and Moss 2001), and that such knowledge is organized by brand personality traits as opposed to brands. That is, with regards to the contentful associations that distinguish one brand from another, the underlying neural representations appear to be akin to previous distributed accounts of conceptual knowledge (Binder et al. 2009; Tyler and Moss 2001) reflecting the complex array of cognitive processes which are engaged.

Interestingly, within this distributed set of brain regions, we found brand personality contents present in both MPFC and LPFC regions (Figure 4). On the surface, the fact that we found brand personality contents in MPFC regions may appear at odds with previous findings in Yoon et al. (2006) that MPFC activity is lower during brand processing than person processing. Both sets of findings, however, are consistent with the notion that MPFC exhibits a gradation of activation levels in person judgment tasks. That is, as opposed to all or none activation, MPFC has been previously shown to exhibit lower activity in judgment of out-group individuals relative to in-group individuals (Volz, Kessler, and von Cramon 2009), and to judgments of more dissimilar individuals relative to more similar individuals (Mitchell, Macrae, and Banaji 2006). Under this interpretation, reduced MPFC activation reflects the fact that brand judgment only weakly draws upon anthropomorphic features and processes. An alternative possible explanation is that these two studies engage fundamentally different aspects of MPFC functioning. For example, whereas locally distributed response patterns in the MPFC reflect brand personality, mean response differences in the MPFC may instead reflect some other process that is known to engage MPFC, for example valuation processes widely observed in neuroeconomic studies (Plassmann et al. 2008; Rangel, Camerer, and Montague 2008). Indeed, this is a general limitation in exploratory reverse inferences, including those using probabilistic meta-analytic techniques such as Neurosynth (Yarkoni et al. 2011). Future studies combining the approach outlined in the current study and those of Yoon et al. (2006) would be needed to address these issues.

More generally, the methods outlined here enable consumer researchers to consider a set of research questions not previously testable, and are centered around the idea that spatially distributed fMRI activity patterns may represent a viable signature of hypothesized psychological constructs (Haynes and Rees 2006; Naselaris et al. 2011). This includes, for example, cases where self-reported perceptions or preferences may be compromised due to factors such as social desirability bias. Existing efforts to control for such biases have largely consisted of randomized response (RR) protocols (de Jong, Pieters, and Fox 2010; Warner 1965). These protocols reduce privacy concerns by using a randomization mechanism to “shroud” the participant’s response, and rely on the credibility of the randomization device and feelings of privacy, which have been challenged in recent years (Chaudhuri and Christofides 2013). In contrast, by eliciting neural responses without any overt behavior, passive viewing experiments such as in the current study may be able to overcome some of these challenges.

With respect to branding, capturing the mental map of brand personality opens the door for studies seeking to address a number of additional questions of interest to consumer researchers and marketers. In particular, by capturing and validating brand personality representations in the brain, a natural next step is to characterize how these representations are affected by marketing actions, and what are the different cognitive processes that act on these representations. This parallels the trajectory of findings in more basic psychological processes such as working memory, where discovering the existence of visual working memory contents in extrastriate regions allowed researchers to ask a number of questions regarding how these representations were affected under different task demands (Chadwick et al. 2010; Lee, Kravitz, and Baker 2013a). For example, it was found that information about object identity was contained in different brain regions depending on whether participants were asked to attend to visual or nonvisual properties of the object (Lee, Kravitz, and Baker 2013b).

One set of questions along these lines involves comparison of different dimensions of brand knowledge, such as brand experience and brand relationships, as well as how these representations differ across consumer segments. Intuitively, whereas brand personality captures traits that consumers project onto brands (Aaker 1997), brand experience captures responses that brands evoke on part of consumers (Brakus, Schmitt, and Zarantonello 2009), and brand relationships capture feelings and episodes that consumers have actually experienced with the brands (Fournier 1998). Moreover, these associations have been shown to differ in important ways across segments such as cultural background (Aaker, Benet-Martínez, and Garolera 2001). It may well be therefore that these constructs are subserved by different mental processes and differ across segments, which have implications for brand managers in designing marketing activity can create or affect these dimensions of brand knowledge.

Finally, future studies extending our approach can begin to quantify extent to which consumers' mental representations of brand personality are affected by marketing actions, a question of clear interest to brand managers. In our current study, we have explicitly assumed that activation patterns elicited by brands remain constant across different repetitions. Although this is likely to be a safe assumption given our stimuli contained some of the most iconic brands in the world, it limited our ability to make inferences on how brand associations and values are acquired and how they evolve over time (Johar, Sengupta, and Aaker 2005; van Osselaer and Janiszewski 2001). Future studies combining our approach with dynamic models of inference updating can therefore begin to trace out the processes by which marketing actions affect multiple dimensions of brand knowledge and preference.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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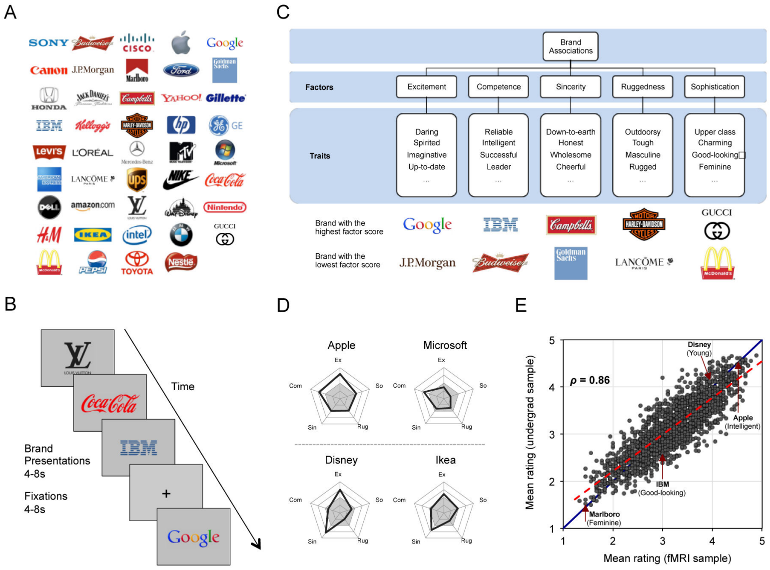


FIGURE 1. Experimental Paradigm And Behavioral Results

(A) A total of 44 brands and their associated logos were used in the experiment, chosen from Interbrand's list of top global brands. **(B)** Subjects engaged in a passive viewing task, and were instructed to think about the characteristics or traits associated with each brand. For each trial, a brand logo was presented for 4-8 seconds on a gray background. **(C)** Quantitative description of brand association was derived using the Aaker brand association framework. For each brand, participant rated a set of 42 traits (e.g., down-to-earth), yielding a set of five latent features via factor analysis. Examples of the extreme brands are presented at bottom to illustrate how brand associations were captured in this framework. **(D)** Radar chart of example brands that reside in the same industry but possess distinct associations (Apple and Microsoft), and those in different industries but possess similar associations (Disney and Ikea). Each vertex indicates a brand personality factor (Ex: Excitement, Com: Competence, Sin: Sincerity, Rug: Ruggedness, So: Sophistication). Vertex the factor score of brand on each dimension. Shaded (unshaded) regions indicate negative (positive) factor scores. **(E)** Mean trait rating of neuroimaging experiment participants were highly correlated with those from an independent pool of undergraduate students (Pearson r=0.86,p<10^{-10}).

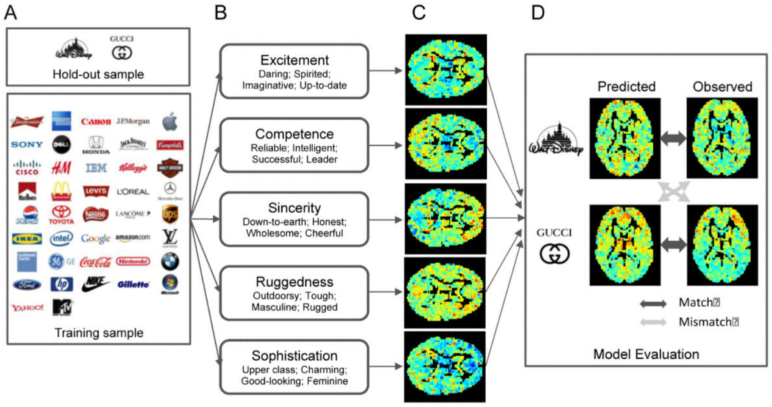


FIGURE 2. Empirical Approach

(A) For each iteration, two brands were held out of the training set, e.g., Disney and Gucci, and model calibration was done using the remaining 42 brands in the training set. **(B)** Neural signatures of brand association were estimated using brands' personality features derived from participants' ratings. **(C)** Learned c_n^v coefficients for the five personality features are depicted in single axial slice with color representing image intensity. **(D)** Cross-validation is completed by using trained neural signatures to predict observed neural responses to hold-out brands. The predicted image for the holdout brand is calculated as a linear combination of the personality features of the holdout brands, weighted by the estimated c_n^v coefficients associated with each feature. This schematic shows predicted and observed fMRI images for Disney and Gucci using axial slice of a single participant.

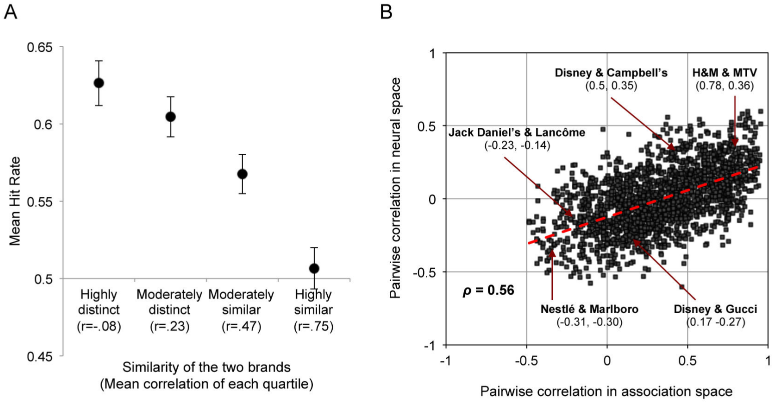
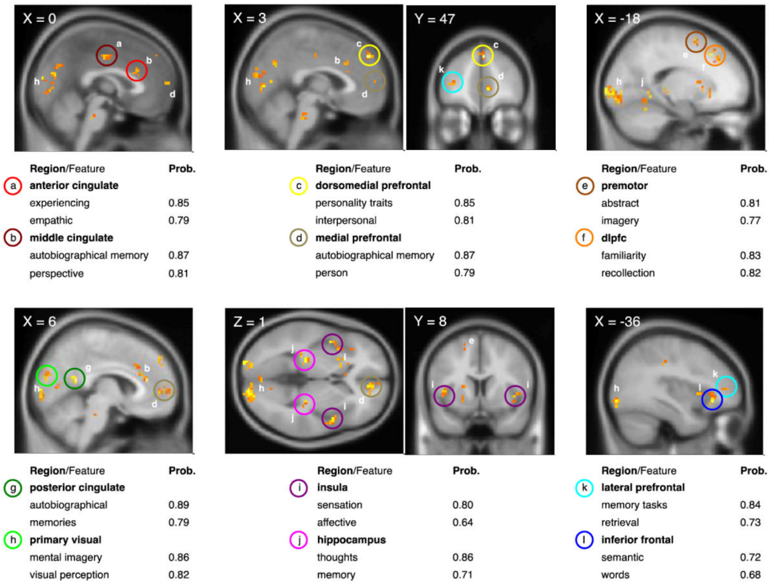


FIGURE 3. Brand Personality Traits Can Be Recovered From Brain Activity

(A) The overall hit rate for holdout classification was 58% (Permutation test $p<10^{-5}$). Separating the brands based on subjective similarity into quartiles as assessed based on correlation of trait ratings, we find a significant relationship between hit rate and subjective similarity. That is, performance in classification is improved when brands are more dissimilar. When brands are highly similar (mean Pearson $r=0.75$), classification rate is at chance. Errorbars indicate SEM. **(B)** To formally compare similarity between neural and psychological measures of brand associations, we plotted, for each brand pair, the correlation between predicted and observed brain images evaluated over the 500 image voxels with the most stable responses across training presentations (y-axis) against similarity in brands' psychological properties as measured using correlation of trait ratings (x-axis). We found that strength of neural correlation is robustly modulated by the similarity of brands' psychological properties (Pearson $r=0.56, p<10^{-7}$). That is, brands that are more similar in trait ratings were also more highly correlated at the neural level.



Region/Feature	Prob.
ⓐ **anterior cingulate**	
experiencing	0.85
empathic	0.79
ⓑ **middle cingulate**	
autobiographical memory	0.87
perspective	0.81

Region/Feature	Prob.
ⓒ **dorsomedial prefrontal**	
personality traits	0.85
interpersonal	0.81
ⓓ **medial prefrontal**	
autobiographical memory	0.87
person	0.79

Region/Feature	Prob.
ⓔ **premotor**	
abstract	0.81
imagery	0.77
ⓕ **dlpfc**	
familiarity	0.83
recollection	0.82

Region/Feature	Prob.
ⓖ **posterior cingulate**	
autobiographical	0.89
memories	0.79
ⓗ **primary visual**	
mental imagery	0.86
visual perception	0.82

Region/Feature	Prob.
ⓘ **insula**	
sensation	0.80
affective	0.64
ⓙ **hippocampus**	
thoughts	0.86
memory	0.71

Region/Feature	Prob.
ⓚ **lateral prefrontal**	
memory tasks	0.84
retrieval	0.73
ⓛ **inferior frontal**	
semantic	0.72
words	0.68

FIGURE 4. Brand Personality Contents Are Distributed Widely Across The Brain

We show the slice view of the most accurately predicted voxels, i.e., voxels with highest correlation between out-of-sample prediction rates and actual activations for the average participant. Each panel shows clusters containing at least 10 contiguous voxels where predicted-actual correlation is significantly greater than zero, with $p<0.05$ from the permutation test (Table 1). To make inferences about cognitive processes subserved by these regions, we used the meta-analytic tool Neurosynth (Yarkoni et al. 2011) to generate the probability that a specific cognitive process is engaged given activation in a particular brain region. For example, given specific voxel location of the observed activation in the dorsomedial prefrontal cortex (cluster c), there is a 0.85 probability that the term "personality traits" was used in a study given the presence of reported activation.

TABLE 1

Voxel locations of brain regions where predicted neural response for held-out brands were significantly correlated with the observed neural responses.

Cluster		**Voxel**[3]				
Size[1]	**Corr**[2]	**X**	**Y**	**Z**	**L/R**[4]	**Region**
184	0.65	18	−94	−5	R	Lingual Gyrus
11	0.63	−12	38	55	L	Superior Frontal Gyrus
15	0.6	51	11	−8	R	Superior Temporal Gyrus
23	0.57	6	−52	16	R	Posterior Cingulate
145	0.55	−12	−97	−8	L	Lingual Gyrus
36	0.54	6	35	16	R	Anterior Cingulate
17	0.53	3	47	40	R	Medial Frontal Gyrus
15	0.5	−18	26	43	L	Superior Frontal Gyrus
10	0.49	36	−34	−2	R	Sub-Gyral
14	0.48	−21	11	58	L	Middle Frontal Gyrus
14	0.47	−45	2	1	L	Insula
16	0.47	−3	−7	43	L	Cingulate Gyrus
23	0.46	51	2	−2	R	Superior Temporal Gyrus
14	0.46	−36	29	−8	L	Inferior Frontal Gyrus
12	0.46	−9	26	28	L	Cingulate Gyrus
11	0.45	21	−37	−5	R	Parahippocampal Gyrus
26	0.44	9	47	1	R	Medial Frontal Gyrus
25	0.43	3	−79	4	R	Lingual Gyrus
32	0.42	−3	−79	22	L	Cuneus
13	0.42	−33	53	13	L	Superior Frontal Gyrus
14	0.4	27	41	31	R	Superior Frontal Gyrus
28	0.39	−12	26	−5	L	Caudate
10	0.37	3	−64	28	R	Precuneus

[1] Cluster size (voxels).

[2] Correlation coefficient between the predicted and the observed brain images.

[3] Voxel location (X, Y, Z) in MNI coordinate (mm).

[4] Laterality of activation (L = left hemisphere, R = right hemisphere).