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By

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Abstract

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Marketing theory and practice have become increasingly customer-centered in recent decades. To that end, marketers, consumer researchers, and the lay public alike have begun to take special interest in how understanding the human brain can help them better understand consumers. Despite advances in knowledge of how the brain represents simple goods such as those involving primary rewards, however, there is great difficulty in extending this understanding to more complex goods typical of modern human society, and in particular how the brain represents the set of intangible characteristics resulting from social and cultural influences, for example, the intangible characteristics captured by a good's brand. Here we combine newly available machine learning techniques with functional neuroimaging data to characterize the set of processes that give rise to the intangible associations people have with brands. Our 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

Marketing theory and practice have become increasingly customer-centered in recent decades (for example, Keller 1993; Rust, Zeithaml, and Lemon 2004; Lee et al. 2015). Emerging techniques in neuroscience, therefore, have been widely viewed as potentially allowing consumer researchers to better understand consumers by directly accessing their mental contents (Ariely and Berns 2010; Plassmann, Ramsøy, and Milosavljevic 2012; Yoon et al. 2012). 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. Although still preliminary and incomplete, existing studies using functional neuroimaging techniques have already made important inroads in addressing some of these core questions (McClure et al. 2004; Plassmann et al. 2008; Hedgcock and Rao 2009; Ariely and Berns 2010; Brownell 2013; Smidts et al. 2014). 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. 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".

Here we take an important step toward enabling consumer researchers to address both "what" and "where"-types of questions using brain imaging data (Kriegeskorte, Goebel, and Bandettini 2006; Kay et al. 2008; Mitchell et al. 2008). Specifically, by applying newly available machine learning tools to functional neuroimaging data, we sought to decode the mind of consumers. The central insight of this approach is to use cross-validation techniques to consider whether a distributed set or "pattern" of brain activity, possibly distributed across many regions, contains some set of information predicted by cognitive and behavioral theories (Kriegeskorte et al. 2006; Poldrack 2011).

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. More specifically, the number of concepts and theoretical processes that have been hypothesized has grown enormously in recent years, but this increased sophistication in dealing with cognitive processes has remained at the conceptual level (Lynch and Srull 1982). It has generally not been accompanied by methodologies that are capable of diagnosing such processes. By identifying distinct neural components of a decision process, we sought to provide a way to test these concepts and theoretical processes, so that existing theory can be refined and improved.

Just like knowledge in neuroscience can potentially enrich research on consumer behavior, integrating consumer research with neuroscience offers tremendous potential to fully characterize the decision-making processes. Research during the past decade has greatly expanded our knowledge of the neural basis of human decision-making (Glimcher and Rustichini 2004; Sugrue, Corrado, and Newsome 2005; Montague, King-Casas, and Cohen 2006; Rangel, Camerer, and Montague 2008). An integral part of this effort has been the application of functional neuroimaging data to a simple yet powerful framework where people make decisions by evaluating and maximizing subjective value associated with competing alternatives (Sugrue et al. 2005; Camerer 2008; Plassmann et al. 2008). However, a particularly challenging aspect of characterizing decision-making processes beyond stylized laboratory settings is the sheer variety of objects that people place value upon in modern human societies, many of which have no intrinsic value nor parallel among other species (McClure et al. 2004; Plassmann et al. 2008; Palmer, Schloss, and Sammartino 2013).

For example, people routinely place value on one brand over another, even in cases where the underlying goods are identical or nearly identical. Using Coca-Cola and Pepsi as a particularly salient case, previous studies have shown that knowledge of the brand robustly influences choice behavior (Woolfolk, Castellan, and Brooks 1983), and, at the neural level, modulates value representation in reward regions (McClure et al. 2004; Koenigs and Tranel 2008). Largely missing from these studies, however, is how the brain represents the rich set of thoughts, feelings, and images that people associate with brands like Coke and Pepsi. That is, it remains unclear how the set of intangible characteristics associated with goods are represented at the neural level, the representational space underlying these characteristics, and how they ultimately translate to downstream effects on reward representation and choice behavior (Camerer 2008; Rangel et al. 2008). Here we sought to take a first step toward addressing these issues by characterizing neural representation of an important class of intangible characteristics captured by a good's brand.

In the dissertation, we combine newly available machine learning techniques with functional neuroimaging data to characterize the set of processes that give rise to the intangible associations people have with brands. In the first chapter, we bring the question from "where" to "what". Instead of localizing the brain areas correlates with brands' characteristics, we propose to use decoding methods to read out the contents about a brand containing in the brain (Haynes and Rees 2006). In the second chapter, we show that a brand's person-like characteristics can be captured by the weighted activity across a widely distributed set of brain regions previously implicated in reasoning, imagery, and affective processing. In the third chapter, we utilize the method of decoding to compare different models of mental representation of brands using brain activities. We find that patterns of brain activities similar to semantic knowledge are associated with brands' person-like characteristics, while brain activities similar to episodic memory are associated with consumer experience about a brand.

Chapter 1

From “Where” to “What”: Decoding Approach

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 (Gardner and Levy 1955; Keller 1993; Aaker 2009). 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 (Keller 2003; Aaker 2012).

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 (Bettman 1970; Alba and Hutchinson 1987; Coulter and Zaltman 1995; Keller 2003). This has resulted in a set of sophisticated typologies that provides rigorous scientific characterization to these complex perceptions. One canonical typology, for example, involves the characterization of the widely held notion that consumers endow brands with a set of human-like characteristics akin to personality (Levy 1959; Aaker 1997). 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 (Keller and Lehmann 2003; Johar, Sengupta, and Aaker 2005). 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 (Haire 1950; Coulter and Zaltman 1995; Ariely and Berns 2010). 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 et al. 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 (Zaltman 1997; Keller 2003). 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.

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 et al. 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 1988; 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.

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; Norman et al. 2006; Mitchell et al. 2008). In comparison to “where”-type questions that are the focus of traditional localization approaches, we sought to address the “what”-type questions in consumer neuroscience.

Chapter 2

Decoding the Neural Representation of Brand Personality

2.1 INTRODUCTION

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. To characterize the set of processes that give rise to these associations, here we take an important step toward enabling consumer researchers to address both “what” and “where”-types of questions using brain imaging data (Kriegeskorte et al. 2006; Kay et al. 2008; 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 et al. 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 et al. 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; Tusche, Bode, and Haynes 2010; Murawski et al. 2012; van der Laan et al. 2012). 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 (Tyler and Moss 2001; Mitchell et al. 2008).

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 et al. 2006; Schaefer and Rotte 2010), semantic memory retrieval (LPFC, McClure et al. 2004; Yoon et al. 2006; Klucharev, Smidts, and Fernández 2008), affective processing and interoception (insula, Bruce et al. 2013), episodic and spatial memory (hippocampus, McClure et al. 2004; Esch et al. 2012), 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.

2.2 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 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 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 (Haynes and Rees 2006; Clithero, Carter, and Huettel 2009).

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:

<u>i. Extracting neural responses to brands:</u> 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 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.

<u>ii. In-sample model training:</u> 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:

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

where $f_{n,j}$ is the value of the n^{th} personality feature for brand j, and c_n^v is a scalar parameter that specifies the degree to which the n^{th} 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 $y_j^v = c_1^v f_{1,j} + c_2^v f_{2,j} + \cdots + c_n^v f_{n,j}$ (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.

<u>iii. Model prediction using hold-out sample:</u> 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 Appendix for details).

<u>iv. Significance testing:</u> 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.

2.3 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 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 Appendix). Further inspection of the factor loadings showed that our results largely replicated those of previous studies (Figure S2 in 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 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.

2.4 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 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 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 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 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 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.

2.5 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 et al. 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; Norman et al. 2006; Mitchell et al. 2008). 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; Norman et al. 2006; Mitchell et al. 2008), 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 et al. 2006; Yoon et al. 2006; Schaefer and Rotte 2010), 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 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) (Tyler and Moss 2001; Binder et al. 2009), 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 (Tyler and Moss 2001; Binder et al. 2009) 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 et al. 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 (Warner 1965; de Jong, Pieters, and Fox 2010). 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 2013). 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 et al. 2013).

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-Martinez, 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 (van Osselaer and Janiszewski 2001; Johar et al. 2006). 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.

Chapter 3

Comparing Brand Personality and Brand Experience by Decoding their Neural Representation

3.1 INTRODUCTION

Memory plays a major role in consumer choice (Alba, Hutchinson, and Jr. 1991; Schacter 1999). What people buy is heavily dependent upon what information is in memory and how this information is organized (Bettman 1979). Researchers have been studying the influence of memory on consumer decision making, especially the way information is retrieved from memory (Lynch and Srull 1982). Despite these successes, research in consumer psychology has been largely silent on the specific processes by which consumer memory are generated and organized (Keller and Lehmann 2003; Johar et al. 2005).

For example, brands, which can be viewed as a collection of information people associated with goods or companies. Brand memory plays an important role on consumer behavior (for example, Nedungadi 1990; Morrin 1999). A significant challenge in studying brand memory lies in their complexity and the fact that they depend on the way people access their memory associated with brands. When people retrieve a brand from their memory, they may think about the generic knowledge descriptive of the brand (Baumgartner, Sujan, and Bettman 1992), and/or a recollection of episodes from their past experiences with it (Tulving 2002). For example, when thinking the brand, Disney, people may think about the features "family-oriented, friendly, and cheerful", and/or they may remember "I feel like a child; I feel warm and safe; I want to discover things; I feel part of the magic" (Brakus et al. 2009). These two different information-processing systems retain different aspects of information about brands (Tulving 1972). However, it remains unclear how these two different sets of information associated with brands are represented at the neural level and the representational space underlying these information (Camerer 2008; Rangel et al. 2008). Here we sought to take a first step toward addressing these issues by using brain imaging techniques to test our ability to infer consumer memory of brands using two different sets of psychological features to model the underlying representational space, in order to characterize the set of processes that give rise to these two different classes of brand memory.

First, we sought to quantitatively characterize the two information-processing systems using typologies that provide rigorous scientific characterization to these complex perceptions from consumer researchers (Bettman 1970; Alba and Hutchinson 1987; Coulter and Zaltman 1995; Keller 2003). There are two constructs that fit well to conceptualize the two information-processing systems. The first one is a canonical typology involving the characterization of the widely held notion that consumers endow brands with a set of human-like characteristics akin to personality (Levy 1959; Aaker

1997). The construct of brand personality can be viewed as generalized representations of brands formed from numerous prior experiences. On the other hand, the recollection of episodes from people past experiences associated with brands can be conceptualized with brand experience, which is conceptualized as sensations, feelings, cognitions, and behavioral responses evoked by brand-related stimuli that are part of a brand's design and identity, packaging, communications, and environments (Brakus et al. 2009). Whereas brand personality captures traits that consumers project onto brands (Aaker 1997), brand experience captures responses that brands evoke on part of consumers (Brakus et al. 2009).

Second, we sought to relate the two information-processing systems, brand personality and brand experience, to brain imaging data. More specifically, we sought to locate brain regions where the activity patterns contain information about brand personality or brand experience. Instead of using classical localization approaches that focus on "where"-type questions, we focus on "what-"type of question using model-based decoding approach to show that the information content is actually contained within the set of identified brain regions (Kriegeskorte and Bandettini 2007). Distinguished from those that do not assume some underlying model of the representational space (for details, see Haynes and Rees 2006; Poldrack 2011), we identify the particular brand a person is thinking about based the evoked brain responses, by requiring brand personality or brand experience 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. Similarly, 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 experience in the brain, and use this relationship to infer whether that person is thinking about Apple or Microsoft. Moreover, we ask whether the brain regions that contain information about brand personality are different from the brain regions that contain information about brand experience.

Specifically, we use a model-based searchlight decoding approach to determine the locations in the brain where there is a statistical dependency between the experimental conditions (the overall psychological features of brands, either personality or experience) and the regional spatiotemporal activity patterns (Kriegeskorte and Bandettini 2007). A continuous information-based mapping is performed with a multivariate searchlight, in order to discover regions carrying information about brand personality or brand experience (Kriegeskorte and Bandettini 2007). These multivariate methods can help us to characterize cognitive processes of the two different types of mental representation of brands.

3.2 METHODS

fMRI Experiment. 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. Participants 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). 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. Each participant was paid $70 in cash upon completion of the experiment. All informed consent was obtained as approved by the Internal Review Board at University of California, Berkeley.

The fMRI data set is the same as which in Chapter 2. However, we recruited an independent set of subjects to judge the characteristics of the brands, for both personality features and experience features.

Behavioral Experiment. We recruited undergraduate students for a behavioral-only study in exchange for course credits. These participants either completed an online questionnaire of the brand personality scale or the brand experience scale with the same set of the 44 brands used in the fMRI study. 94 students completed the personality survey, and each of them judged the descriptiveness of the 42 traits toward randomly selected 22 brands (Aaker 1997), with a five-point scale from not at all descriptive (rating=1) to extremely descriptive (rating=5) (Figure 5A). The other 165 students completed the experience survey, and each of them judged the descriptiveness of the 12 brand experience items toward randomly selected 11 brands. The 12-item brand experience scale (Brakus et al. 2009) involved judgment of the descriptiveness of 12 items to each brand (Figure 5B), with a seven-point scale from not at all descriptive (rating=1) to extremely descriptive (rating=7).

Behavioral Data Analysis. To characterize personality/experience features associated with our brands using participant ratings, we used a factor analytic approach to summarize variation in trait ratings and reduce collinearity issues. For personality (experience) survey, mean ratings of personality traits (experience items) 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. Each brand was re-expressed in terms of its personality/experience vector.

fMRI Data Preprocessing. Image data were preprocessed 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. Data were left unsmoothed to preserve local voxel information.

To identify the representative fMRI image of a brand, we used the procedure outlined in Mumford et al. (2012) using 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). 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.

fMRI Data Analysis. To localize the brain regions that contain information of thinking about brands' personality features or experience features, a whole-brain MVPA searchlight analysis was performed to test the classifier's ability to discriminate the two previously unseen brands using different sets of independent variables (personality or experience) (Kriegeskorte et al. 2006). For each voxel v_i, we defined a sphere of 10 mm radius centered on v_i. The fMRI data from this cluster were then used for training and testing the model, iterating over all possible pairwise combination of the 44 brands. This procedure was repeated for every voxel in the brain, and results were mapped back to yield a whole brain accuracy map for each subject.

For each voxel v_i, we defined a sphere of 10 mm radius centered on v_i. The following procedure was repeated for every voxel in the brain. For each iteration, two brands were held out of the training set, and the model was trained using the remaining 42 brands. Specifically, training involved regressing activation level of each voxel on the set of personality or experience features of the training brands obtained from the factor analysis. The derived maximum likelihood estimates were used as c_n^v terms, which were then combined with the personality or experience factor scores of each hold-out brand to form its a predicted fMRI pattern. This leave-two-out train-test procedure was iterated 946 times, leaving out each of the possible brand pairs. Following training, the computational model was evaluated by comparing these predicted fMRI pattern to the observed fMRI pattern of the two hold-out brands, evaluated over the image voxels within each of the searchlight. Finally, the average performance within the searchlight was mapped back to yield a whole brain accuracy map for each subject.

The procedure was similar to which in Chapter 2. The only difference is that the model is trained and tested with voxels within the sphere centered on each voxel in the brain, instead of selecting the most stable voxels.

3.3 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. 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 (86.4%) of the variance was captured by 5 factors. Further inspection of the factor loadings showed that our results largely replicated those of previous studies (Figure 5A). For example, the first factor loaded highly on the traits "trendy", "cool", and "good looking"—commonly referred to as the Excitement factor. The second factor, referred as Sincerity, loaded highly on traits such as "wholesome", "sincere", 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 personality characteristics participants associate with these brands.

Brand Experience Factor Structure. Second, we characterized the set of experience feature $f_{n,j}$ associated with our brands using participant ratings on the set of items outlined in the Brakus framework. Similarly, we used a factor analytic approach to summarize variation in ratings and reduce collinearity issues. We found that a substantial proportion (85.7%) of the variance was captured by 3 factors (Figure 5B). The first factor loaded highly on the items "this brand makes a strong impression on my visual sense or other senses" and "this brand is an emotional brand". We referred this factor to the sensory/affective factor. Disney has the highest sensory/affective factor score, while Cisco has the lowest one. The second factor, referred as cognitive factor, loaded highly on items such as "this brand stimulates my curiosity and problem solving". Google has the highest cognitive factor score, while Nestlé has the lowest one. We referred the third factor to the behavioral factor, and Nike has the highest behavioral factor score. Using this factor analytic framework, we characterize each brand as a vector of experience features consisting of these three factors that summarizes the set of experience participants associate with these brands.

Personality and Experience Contents are Distributed Differently in the Brain. Using results from the factor-analytic model, we next sought to relate personality/experience 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. We used a whole-brain searchlight approach to locate brain regions that contain information about brand personality or brand experience.

To compare brand personality and brand experience, we sought to characterize the set of brain regions where the prediction accuracy is significantly different using the two sets of variables. To do so, we performed a paired T tests at each voxel location of the 17 individual accuracy maps for personality and the other 17 individual accuracy maps for experience. We found that the set of predictive voxels for personality and for experience were distributed differently throughout the brain (Figure 6, Table 2-3). To better understand the brain regions that contain more information about personality or experience, we threshold the T statistics map with $p<0.01$. We find that activation patterns within DLPFC, DMPFC, TPJ and anterior insula can distinguish the previous unseen brands using personality features significantly better than using experience features (Figure 7; Table 2). On the contrary, activation patterns within posterior insula, hippocampus, and ACC perform better using experience features than using personality features (Figure 8; Table 3).

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 7-8). We found that the brain regions containing information about personality distributed across a number of types of cognitive functions, but in particular those implicated in previous studies of semantic knowledge (DLPFC, DMPFC, TPJ and anterior insula) (Figure 7; Table 2) (Binder et al. 2009). On the other hand, the brain regions containing information about experience distributed across a number of brain regions cognitive functions, which implicated in previous studies of episodic knowledge (posterior insula, hippocampus, and ACC) (Figure 8; Table 3) (Tulving 2002).

3.4 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). Here we take an important step toward bridging this gap, and begin to provide a neuroscientific framework to address the question of the set of thoughts and feelings that occur when people think or interact with the brands. 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).

First, brand personality and brand experience exist a priori inside the mind of the consumer. We found that we were able to predict what brand consumers were thinking about solely based on the relationship between brand personality/experience and brain activity. In particular, because participants in our study were not prompted on thinking about traits such as "daring", "reliable", and "wholesome", nor thinking BOUT their experience associate with brands, our likelihood of predicting what brands participants are thinking of should be at chance if such associations did not come across the consumers' thoughts.

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. Moreover, we found that the activations associated with brand personality were distributed across a number of types of cognitive functions, but in particular those implicated in previous studies of semantic knowledge (Binder et al. 2009). On the other hand, the activations associated with brand experience were distributed in the brain, in particular those implicated in previous studies of episodic memory (Tulving 2002; Hassabis et al. 2007).

The two distinguishable brain activity patterns coincide with the two information-processing systems that retain different aspects of information (Tulving 1972), semantic memory and episodic memory. Semantic memory associated with brands can be viewed as abstract or generic knowledge descriptive of brands (Baumgartner et al. 1992), and the brand personality construct can be viewed as an approximate of the semantic memory of brands. On the other hand, episodic memory associated with brands can be viewed as a recollection of episodes from one's past experience with brands (Tulving 2002), and the brand experience scale can conceptualize the episodic memory people have with brands.

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). The whole-brain searchlight MVPA can help us identify brain regions that contain information of different models of the mental representation of brands, instead of simply comparing brain activities when people perform different recall tasks.

Conclusion

In my dissertation, we employ brain imaging and machine learning techniques to decode the mind of consumers. Specifically, we are able to read out the information about brands containing in the brain. We find 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. Furthermore, we show that there are two different systems of brand memory, one as episodic memory captured by the brand experience construct, and the other as semantic memory captured by the brand personality construct.

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.

*This dissertation contains co-authored materials with Professor Ming Hsu and Professor Leif Nelson.

Figures

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 $r = 0.86, p < 10^{-10}$).

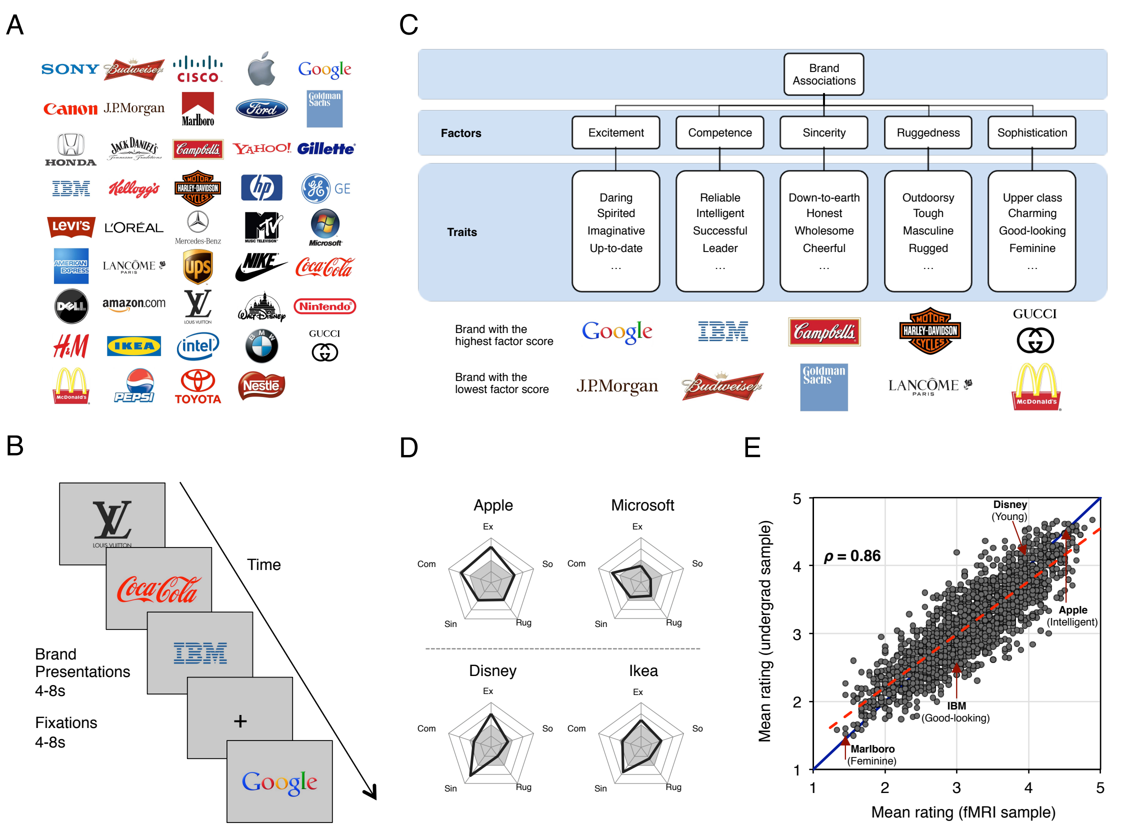


FIGURE 2. Empirical Approach

(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.

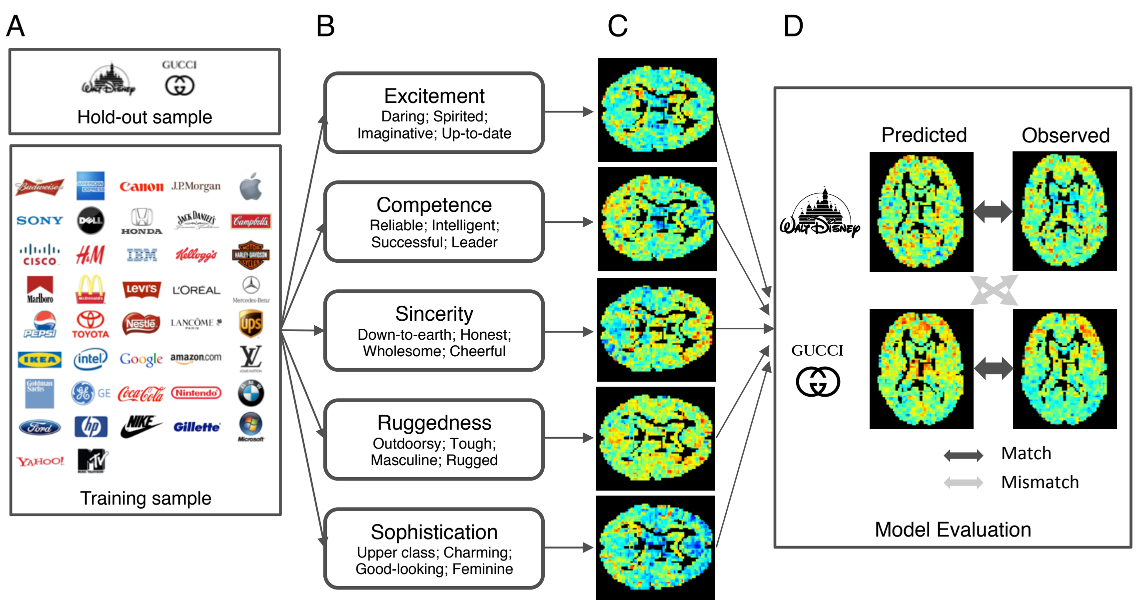


FIGURE 3. Brand Personality Traits Can Be Recovered From Brain Activity

(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.

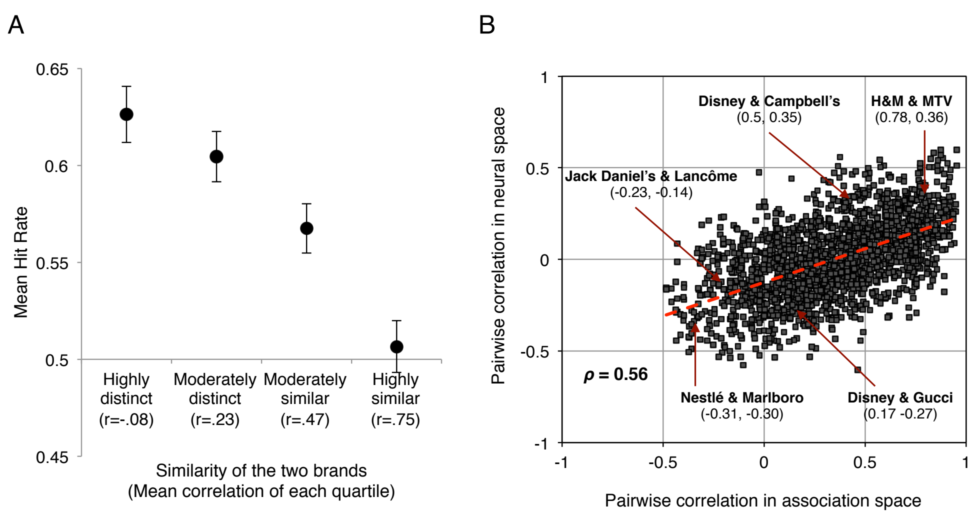
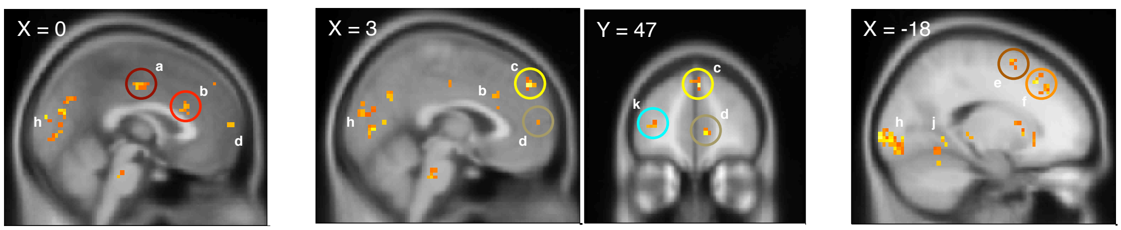


FIGURE 4. Brand Personality Contents Are Distributed Widely Across The Brain

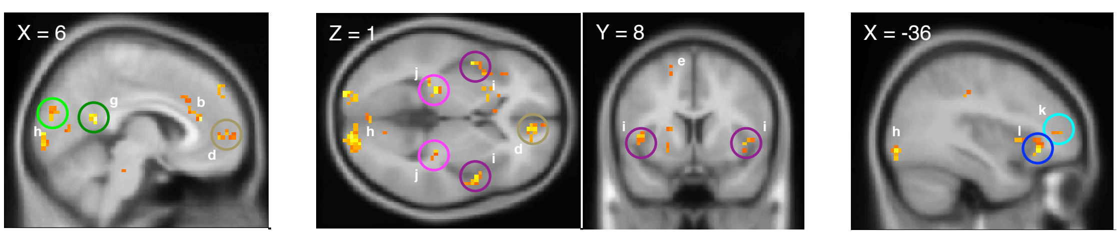
We show the slice view of the most accurately predicted voxels, i.e., voxels with highest correlation between out-of-sample prediction rates and actual activations for the average participant. Each panel shows clusters containing at least 10 contiguous voxels where predicted-actual correlation is significantly 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.



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

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

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



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

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

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

FIGURE 5. Behavioral Responses of Brand Personality and Brand Experience

We use subjects' ratings of the descriptiveness of personality traits and experience items to characterize the psychological features of brands. **(A)** (Top) Personality traits used in the survey. (Bottom) The factor analysis and the criteria yielded five factors, labeled as excitement, sincerity, competence, ruggedness, and sophistication. Further inspection of the factor loadings showed that our results largely replicated those of previous studies **(B)** (Top) Experience items used in the survey. (Bottom) The factor analysis and the criteria yielded three factors, labeled as sensory/affective, intellectual, and behavioral.

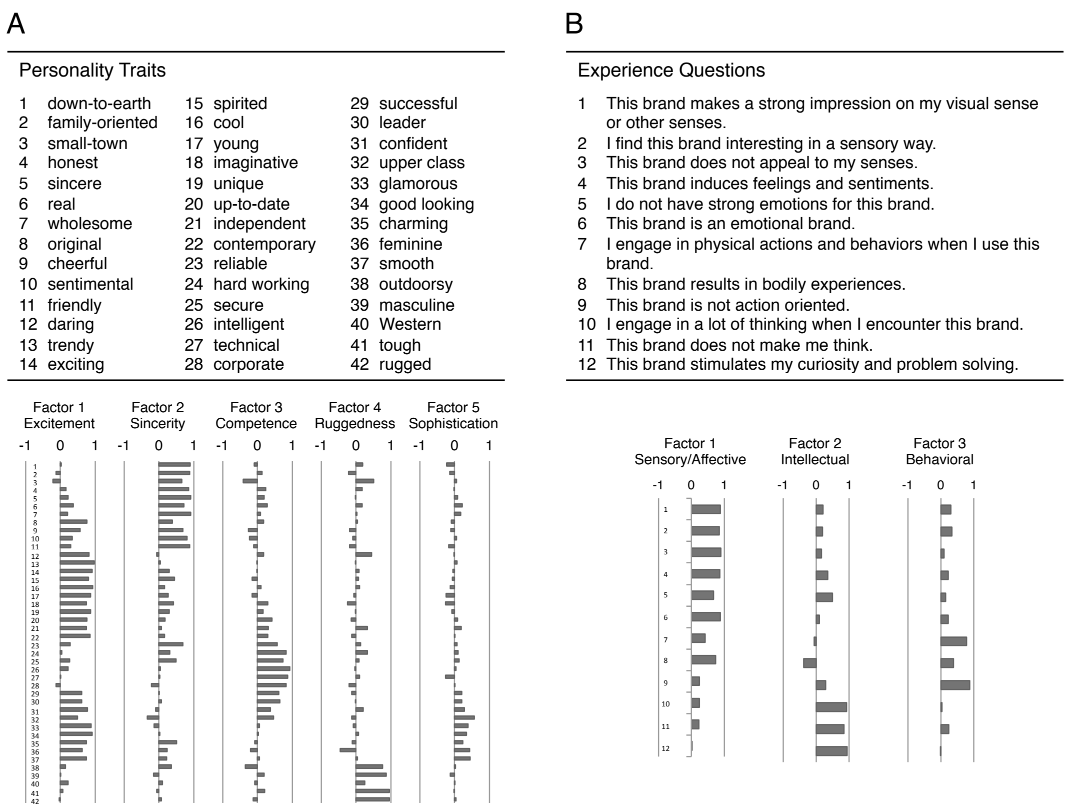


FIGURE 6. T Statistics Map for Comparison between Personality and Experience

For each voxel centered on the 10mm sphere searchlight, the resulting map shows how well the multivariate signal in the local spherical neighborhood differentiates the previous unseen brands, comparing using brand personality to model the psychological features of brands to using brand experience to model the psychological features of brands. Paired T tests were performed at each voxel location of the individual accuracy maps for personality and the individual accuracy maps for experience from whole-brain decoding using an MVPA searchlight approach. Colors indicate t values from a voxelwise paired t test comparing decoding accuracy of the two models. Warm colors show the brain regions where the personality model performs better than the experience model. Cold colors show the brain regions where the experience model performs better than the personality model.

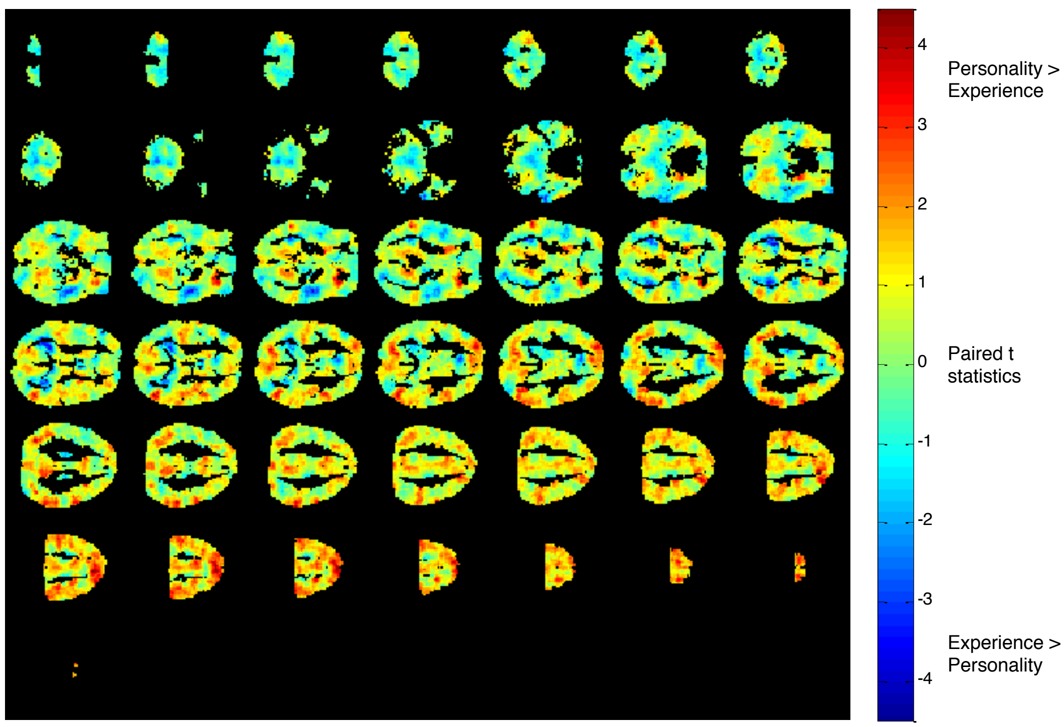
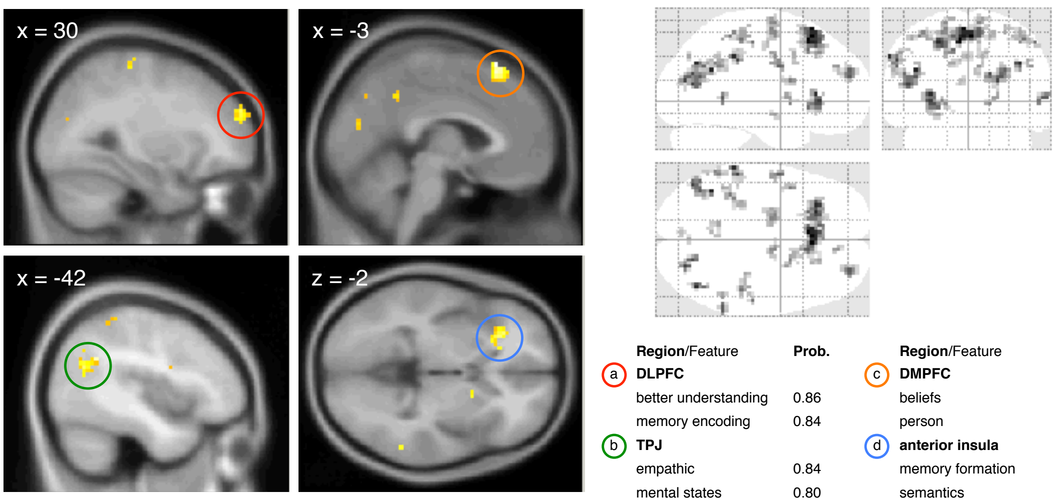


FIGURE 7. Brain Regions Where Personality Significantly Performs Better

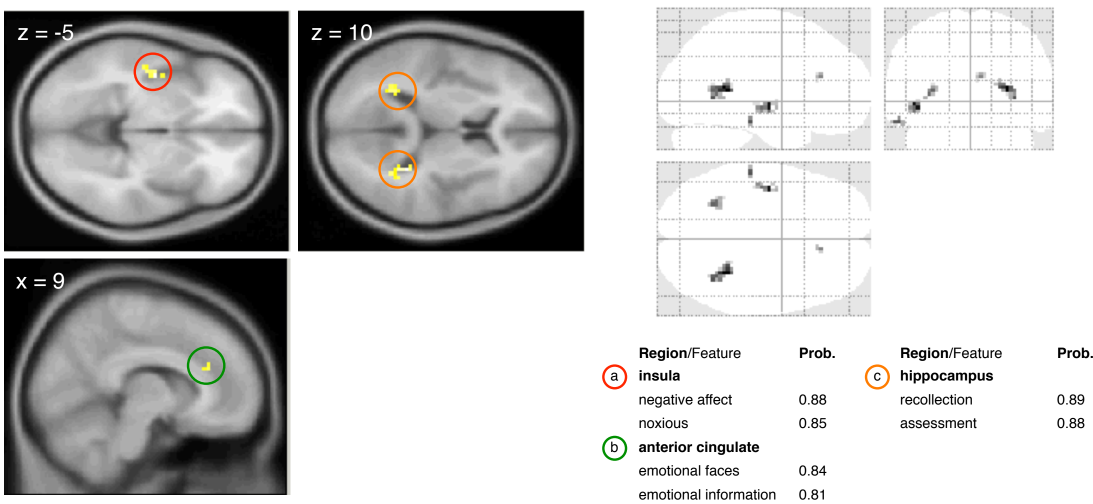
We threshold the whole-brain t-statistics map in Figure 6 to get the brain regions where using the personality model significantly performs better than using the experience model (results were considered statistically significant at $p < 0.01$). We find that compared to brand experience, information about personality contains in dorsolateral prefrontal cortex (DLPFC), dorsomedial prefrontal cortex (DMPFC), temporoparietal junction (TPJ), and anterior insula. These brain regions are usually associated with semantic memory.



Region/Feature	Prob.	Region/Feature	Prob.
a **DLPFC**		c **DMPFC**	
better understanding	0.86	beliefs	0.88
memory encoding	0.84	person	0.86
b **TPJ**		d **anterior insula**	
empathic	0.84	memory formation	0.87
mental states	0.80	semantics	0.81

FIGURE 8. Brain Regions Where Experience Significantly Performs Better

We threshold the whole-brain t-statistics map in Figure 6 to get the brain regions where using the experience model significantly performs better than using the personality model (results were considered statistically significant at $p < 0.01$). We find that compared to brand personality, information about experience contains in posterior insula, hippocampus, and anterior cingulate cortex (ACC). These brain regions are usually associated with episodic memory.



Tables

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).

TABLE 2

Voxel locations of brain regions shown in Figure 7 where the model performance using personality factors was significantly better than using experience factors.

Cluster		Voxel[3]				
Size[1]	T[2]	X	Y	Z	L/R[4]	Region
220	4.77	-6	23	55	L	Superior Frontal Gyrus
72	4.34	-42	-55	28	L	Superior Temporal Gyrus
20	4.32	42	-67	34	R	Precuneus
73	4.3	-30	29	7	L	Inferior Frontal Gyrus
32	4.29	-63	-37	40	L	Inferior Parietal Lobule
38	4.04	24	-76	19	R	Cuneus
42	3.86	27	56	22	R	Superior Frontal Gyrus
15	3.85	60	-46	4	R	Middle Temporal Gyrus
23	3.73	-57	-1	31	L	Precentral Gyrus
44	3.62	45	-31	55	R	Postcentral Gyrus
34	3.55	-39	-40	58	L	Postcentral Gyrus
46	3.46	-21	-4	61	L	Middle Frontal Gyrus
13	3.43	18	8	-2	R	Lentiform Nucleus
11	3.4	9	-4	58	R	Medial Frontal Gyrus
12	3.25	-24	-4	-11	L	Parahippocampal Gyrus
26	3.13	-15	-49	34	L	Precuneus

1. Cluster size (voxels).
2. T values from a voxelwise paired t test comparing decoding accuracy of using personality to experience.
3. Voxel location (X, Y, Z) in MNI coordinate (mm).
4. Laterality of activation (L = left hemisphere, R = right hemisphere).

TABLE 3

Voxel locations of brain regions shown in Figure 8 where the model performance using experience factors was significantly better than using personality factors.

Cluster		Voxel[3]				
Size[1]	T[2]	X	Y	Z	L/R[4]	Region
37	4.03	30	-43	10	R	Caudate
26	3.87	-42	-10	-5	L	Insula
7	3.48	-57	-25	-17	L	Inferior Temporal Gyrus
17	3.34	-30	-55	10	L	Parahippocampal Gyrus
8	3.16	9	32	22	R	Anterior Cingulate

1. Cluster size (voxels).
2. T values from a voxelwise paired t test comparing decoding accuracy of using experience to personality.
3. Voxel location (X, Y, Z) in MNI coordinate (mm).
4. Laterality of activation (L = left hemisphere, R = right hemisphere).

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1. Methods

1.1 General Methods

1.1.1 Subjects

Seventeen adults (6 females) from the San Francisco Bay Area were recruited from Craigslist to participate in the functional magnetic resonance imaging (fMRI) study. Their ages ranged from 26 to 45, with an average of 34 and the standard deviation of 6.5. Informed consent was obtained using a consent form approved by the Internal Review Board at University of California, Berkeley. 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.

1.1.2 Experimental Protocol

We imaged participants' brains with functional magnetic resonance imaging (fMRI) while they underwent a passive viewing task involving 44 well-known brands. The stimuli were 44 brand logos selected from Best Global Brands by Interbrand (Figure 1A), with significant diversity in brand meaning and industry. 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. There were twelve rest periods distributed across the session lasting for 4-8 seconds, during which participants were instructed to fixate on a cross at the center of the screen. In addition, there were six self-paced catch questions, in which participants had to press a particular button using an MRI-compatible button box to continue to the next trial (Figure S1).

When a brand logo was presented, the participants' task was to think about the characteristics or traits associated with the brand. Each participant was free to think about any characteristic or trait they associated with the brands, and there was no attempt to obtain consistency of the associations neither across participants nor across repetition times.

After the scanning session, participants were asked to complete a survey about the brands they saw in the scanner. The survey included the 42-item brand personality scale (Aaker 1997) (Table S1), familiarity, and preference for each brand. The brand personality scale involved judgment of the descriptiveness of 42 traits to each brand, with a five-point scale from not at all descriptive (rating=1) to extremely descriptive (rating=5). Participants reported their familiarity and preference toward the brands from a four-point scale, ranging from dislike/unfamiliar (rating=1), somewhat dislike/unfamiliar (rating=2), somewhat like/familiar (rating=3) to like/familiar (rating=4). We obtained 1,936 ratings in total per participant in the survey.

1.1.3 fMRI Data Acquisitions

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) = 2,000 ms; echo time (TE) = 30 ms; voxel resolution = 3mm×3mm×3mm; FOV read = 192 mm; 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.

1.1.4 Survey of an Additional Sample

An additional sample of 25 undergraduate students completed the survey online on the same set of brands and traits of the brand personality scale for course credits. The average responses of the trait scores were highly correlated among our neuroimaging subjects and the follow-up participants (Figure 1E).

1.2 Behavioral Data analysis

To conceptualize the brands, we first characterized the set of psychological features associated with the brands using participant responses in the survey outlined in Aaker's framework (Aaker 1997). Specifically, we used a factor analytic approach to summarize variation in trait ratings and reduce collinearity issues. First, we averaged responses from all of the participants to calculate the average descriptiveness of each trait to each brand. Then, the average scores were factor-analyzed with SPSS ("IBM SPSS Statistics for Windows, Version 20.0" 2011) using principal components analysis and a varimax rotation. We selected the factors with eigenvalues greater than one, and the solution explained a high level of variance. Finally, each brand can be re-expressed in terms of its feature vector, defined as the strength of association between the brand and the factors (the personality features).

1.3 fMRI Data Preprocessing

Prior to analysis, the images were corrected for slice time artifacts, realigned, coregistered to the subject's T1 image, and normalized to Montreal Neurological Institute coordinates, using SPM8 (Statistical Parametric Mapping, Wellcome Trust Centre for Neuroimaging). Consistent with previous decoding studies, we did not smooth the images.

To identify the representative fMRI image of a brand for the analysis, we followed the methods proposed by Mumford et al. (2012) for event-related designs (Mumford et al. 2012). We first used a general linear model in SPM8 to estimate a single fMRI image for each of the 176 brand presentations, specifically method LS-S in Mumford et al. (2012). The model included the brand of interest as an individual regressor and another regressor consisting of all the other brands and the catch questions. The duration of all of the events was set to be zero. The beta values estimated for the first regressor of the brand of interest was used as the brain activation patterns associated with a brand at a particular repetition time. Alternative procedures to estimate the representative fMRI images were used (section 2.5), but consistent with Mumford et al. (2012), the LS-S method with each event modeled as an impulse function yields the best performance.

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. The fMRI images were then exported to Matlab using Princeton MVPA toolbox. Finally, we applied the individual grey matter mask to include voxels within the grey matter. For each participant, the grey matter mask was created by segmenting the individual's normalized average EPI image using SPM8.

1.4 Decoding Analysis

1.4.1 Overview

We used model-based decoding analysis to predict the fMRI image of a brand j for each of the participant using his/her neural responses to other brands and the personality features of this brand j, following the methods proposed by Mitchell et al. (2008). We assumed that for each participant, the neural response y_j^v in voxel v to brand j is given by $y_j^v = c_1^v f_{1,j} + c_2^v f_{2,j} + \cdots + c_n^v f_{n,j}$, where $f_{n,j}$ is the value of the nth personality feature for brand j, n is the number of personality features, and c_n^v is a scalar parameter that specifies the degree to which the nth personality feature activates voxel v. Notice that the model was estimated independently for each of the participants.

1.4.2 Training the Model

The personality features associated with a brands $f_{n,j}$ were specified with the factors (section 1.2) that quantitatively capture the characteristics or traits associated with the brands. Then, the parameters c_n^v that define the neural signature contributed by the nth personality feature to the vth voxel were estimated. This is accomplished by training the model using a set of observed fMRI images associated with known stimulus brands. Each training stimulus, brand j, was first re-expressed in terms of its personality feature vector $< f_{1,j} \ldots f_{n,j} >$, and multiple regression is then used to obtain maximum likelihood estimates of the c_n^v values; that is, the set of c_n^v values that minimize the sum of squared errors in reconstructing the training fMRI images. Since the number of personality features is less than the number of training examples in our model, this multiple regression problem is well posed and a unique solution is obtained.

Once trained, the resulting computational model can be used to predict the full fMRI activation image for any other brand. Given an arbitrary new brand k, we first expressed the brand with the personality features $< f_{1,k} \ldots f_{n,k} >$ in Aaker's framework. Then, we applied the above formula using the previously estimated values for the parameters c_n^v. The computational model and corresponding theory can be directly evaluated by comparing their predictions for brands outside the training set to observed fMRI images associated with those brands.

1.4.3 Training and Evaluating the Model

The computational model was trained and evaluated using a cross validation approach, in which the model was repeatedly trained using only 42 of the 44 available stimulus items, then tested using the two stimulus items that had been left out. On each iteration, the trained model was tested by giving it the two stimulus brands it had not yet seen (b_1 and b_2), plus their observed fMRI images (i_1 and i_2). We used two ways to evaluate the performance of the model. First, we compared the similarity between the predicted and the observed brain images (section 1.4.4). Second, we required the model to predict which of the two brain images was associated with which of the two brands using a matching procedure described in section 1.4.5. This leave-two-out train-test procedure was iterated 946 times, leaving out each of the possible brand pairs.

1.4.4 Similarity between Predicted and Actual Images

Given a trained computational model, two new brands (b_1 and b_2) and two new images (i_1 and i_2), the trained model was first used to create predicted image p_1 for brand b_1 and predicted image p_2 for brand b_2. The model was evaluated by comparing these predicted fMRI images to the observed fMRI data. We first compared two possibilities: matched pairs (p_1=i_1 and p_2=i_2, dark arrows in Figure 2D) and mismatched pairs (p_1=i_2 and p_2=i_1, light arrows in Figure 2D). 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 mismatched brand.

Because we do not expect every voxel in the brain to be involved in representing the personality features of the brands, only a subset of voxels was used for assessing the similarity between images. This subset of voxels was selected automatically during training, using only the data for the 42 training brands, and excluding the data from the two testing brands. The voxel selection method is described in section 1.4.6.

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). In Figure S5, we compared the average similarity score of matched pairs (p_1=i_1 and p_2=i_2) to the average similarity score of mismatched pairs (p_1=i_2 and p_2=i_1). In Figure 3B, we compared, for each brand pair, the similarity score of predicted and observed brand images (p_A and i_B) against psychological similarity of brands as measured using Pearson correlation coefficient of trait ratings of the two brands.

1.4.5 Matching Predicted to Actual Images

Given the two testing brands (b_1 and b_2) and two observed images (i_1 and i_2), we then required the model to predict which of the two brain images was associated with which of the two brands. The trained model was first used to create predicted image p_1 for brand b_1 and predicted image p_2 for brand b_2. 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. Similarly, we selected a subset of voxels sel(i) of image i to calculate the similarity score. More specifically, the match of the pair of brands is calculated by:

Match ($p_1=i_2$ and $p_2=i_1$) = Correlation (sel(p_1), sel(i_2)) + Correlation (sel(p_2), sel(i_1)).

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.

Pearson correlation coefficient was the first similarity measure we considered, but we subsequently also considered the Euclidean distance of the two vectors and found that the two yielded similar results (Figure S8). All results reported in the current paper use Pearson correlation coefficient.

1.4.6 Voxel Selection

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. The 500 voxels ranked highest by this stability score were used in the similarity test in Figure 3. However, our result is robust when including more voxels in the analysis (section 2.7, Figure S9 & S10) or excluding voxels in the occipital cortex (section 2.8, Figure S11).

Selecting voxels based on the similarity score was the first voxel selection method we considered, but we subsequently also considered selecting voxels based on the significance in the multiple regression equation when training the model. The result is robust for different ways of voxel selection methods. All results reported in the current paper use the voxels selected by the stability scores.

1.4.7 Empirical Distribution to Determine Statistical Significance

The expected chance accuracy of an uninformed model correctly matching two stimuli outside the training set to their two fMRI images is 0.5. The observed accuracies of our trained models, based on 946 iterations of a leave-two-out cross validation train/test regime, are higher than 0.5. Here we used a permutation test to determine the p value based on observed accuracies, in order to reject the null hypothesis that the trained model has true accuracy of 0.5. Given our leave-two-out train/test regime, no closed-form formula is available to assign such a p value. Therefore, we computed the p value based on an empirical distribution of observed accuracies obtained from 10,200 independently trained single-participant models that we expect will have true accuracy very close to 0.5. The empirical distribution of accuracies for these null models was 0.50, with standard deviation 0.06, indicating that observed average accuracy above 0.55 for 17 participants is statistically significant at $p<0.0001$. Below we describe our approach in more detail.

We created this empirical distribution of accuracies by training multiple models using the observed fMRI images for the 44 stimulus brands, but using different brand labels. More specifically, it is a form of permutation test, permuting the 44 stimulus labels. For example, in one model, we used Google's personality features to describe Gucci, IBM's features to describe Campbell's, and so on. In another model, we used an independent scrambled set of the feature scores to describe the brands. Models were trained and tested using the leave-two-out test regime, exactly as elsewhere in this paper, with one minor exception: in these models the 500 most stable voxels were selected using data from all 44 brands, whereas elsewhere this selection of stable voxels was based only on the 42 training brands. This exception was made because it dramatically improves the computational speed.

For each of the 17 participants, we trained and tested 600 such randomly generated models, resulting in 10,200 models in total. The mean accuracy over these models was 0.50, with standard deviation 0.06.

1.4.8 Accuracy Map

The accuracy map in Figure 4 of the main text shows voxel clusters with the highest correlation between predicted and actual voxel values for an average subject. To obtain the accuracy map, we first averaged the fMRI patterns for each brand at each repetition time across 17 subjects. More specifically, we performed the second-level analysis for the subjects' estimated beta files (section 1.3) associated with each brand at each repetition time in SPM8. Using the 176 average brain images, 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 calculated 44 predicted images for the 44 brands, by training a model on the other 43 brands to predict the remaining brand. For each voxel, this produced a set of 44 predicted values. The accuracy score of each voxel was calculated as the Pearson correlation coefficient between this vector of its predicted values and the corresponding vector of its observed values. An image map containing these voxel scores was created.

To determine the significance of the correlation between the predicted vector and the observed vector for a voxel, we took a permutation approach. We computed p values based on an empirical distribution of correlation coefficients obtained from 100,000 independently permuted values. For each voxel, we calculated the Pearson correlation coefficient of the permuted vector and the observed vector. The permuted vectors were created by scrambling the 44 predicted values.

The clusters shown in Figure 4 were then produced using SPM8, to identify clusters containing at least 10 contiguous voxels whose score was greater than the permuted threshold value $p<0.05$.

2. Supplementary Results

2.1 Factor Analysis Results

Using the fMRI subjects' average responses of the descriptiveness of the traits to the brands, our factor analysis and the criteria yielded five factors. We found that a substantial proportion of the variance (86%) was captured by these 5 factors (Table S2), and they were labeled as excitement, competence, sincerity, ruggedness, and sophistication as shown in the factor loadings of traits (Figure S2). Further inspection of the factor loadings showed that our results largely replicated those of previous studies. Using this factor analytic framework, we characterized each brand as a vector of personality features consisting of these five factor scores that summarizes the set of characteristics participants associate with these brands. Each brand thus was re-expressed in terms of its feature vector (Figure S3; Table S3).

2.2 Familiarity and Preference

Our subjects were highly familiar with the brands used in the experiment. The average familiarity score was 3.58 out of 4 across all participants and all brands. Behaviorally, different people had different preference toward the brands. On average, Google (average preference=3.83) and Amazon.com (average preference=3.72) were the most preferred brands, while Goldman Sachs (average preference=1.89) and Marlboro (average preference=1.83) were the least preferred ones. Neurally, we found that activation in striatum was positively correlated with the subject's reported brand preference. Striatum is a region of the brain known to respond to primary and secondary rewards (Fliessbach et al. 2007; Izuma, Saito, and Sadato 2008), and is consistent with the idea that our brains respond to preferences of abstract objects such as brands.

2.3 Individual Results

Given the two testing brands (b_1 and b_2) and two observed images (i_1 and i_2), we required the computational model to predict which of the two brain images was associated with which of the two brands. The average performance of the model for iterating over all of the possible combination of hold-out data across 17 subjects is 58%, compared with 50% if the model performs at chance. For individual subjects, the average hit rate across all of the possible combinations of brand pairs is plotted in Figure S4. Subjects were sorted by the average hit rate.

2.4 Accuracy Map

The accuracy map (Figure 4) shows voxel clusters with the highest correlation between predicted and actual voxel values for an average subject. The clusters contained at least 10 contiguous voxels whose correlation value was greater than the permuted threshold value $p<0.05$. The correlation values, locations, and regions of these voxels are listed in

Table 1. The surface rendering and the glass brain of locations of the most accurately predicted voxels are shown in Figure S6.

2.5 Robustness to Extracting Representative fMRI Response to the 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. More specifically, for each subject, 176 general linear models were estimated, with each model estimating 2 regressors: one regressor for the event of interest (corresponding to a presentation of one particular brand) and one regressor for all other events that are combined into a single nuisance regressor, where each event was modeled as an impulse function (the duration of each event is set to be zero) convolved with a double gamma hemodynamic function.

We run further robustness checks using alternative methods of estimating representative fMRI images. First, we estimate the fMRI images using the LS-S model with the full duration of the events instead of setting the duration to be zero. Second, we estimate the fMRI images using the "standard" general models, where all events of interest are modeled in one general linear model per subject. Consistent with Mumford et al. 2012, the prediction rates are somewhat worse than using the duration 0 LS-S model, but remain quite significant ($p<0.005$, Figure S7A). Other features, such as modulation by psychological similarity, remain qualitatively unchanged (Figure S7B).

2.6 Robustness to the Measure of Psychological Similarity of Brands

We examined the relationship between the psychological organization of brands and the discriminability of the associated brain images in Figure 3, where the psychological similarity of brands were measured by the Pearson correlation coefficient of the averaged trait ratings of the 42 items in the survey. It is not the only way to measure the similarity of brands' psychological features. For example, instead of correlations of traits, we calculated the similarity as the Euclidean distance between brands' feature vectors of the five factor scores. Our results are robust when using the Euclidean distance between brands in association space (Figure S8). More specifically, the difference in correlation between the matched brain images and the mismatched brain images is larger when there is a larger Euclidean distance between the two brands' feature vectors (Figure S8A). Also, the strength of neural correlation between predicted and observed brain images is robustly modulated by the similarity of brands' psychological features (Figure S8B). Finally, separating the brands based on subjective similarity into quartiles as assessed based on Euclidean distance of factor scores, we find a significant relationship between hit rate and subjective similarity (Figure S8C).

2.7 Robustness to Varying Number of Voxels Used in Decoding

The main result comes from comparing the predicted and observed brain images using 500 most stable voxels (section 1.4.6) selecting from 40,000-50,000 voxels in the whole brain. As a robustness check, we ran the analysis including different numbers of voxels. More specifically, we compared our results of discriminative accuracies and the relationship between the psychological organization of brands and the correlation between predicted and observed brain images, using 500, 1000, 5000, and 25,000 voxels with the highest stability scores. Our result is robust when more voxels were included. First, the overall hit rate for hold-out classification did not drop significantly when more voxels were included in the comparison between the predicted and the observed brain images (Figure S9). Second, the significant relationship between hit rate and subjective similarity of brands was also robust when different numbers of voxels were included (Figure S9). Finally, we found that strength of neural correlation is robustly modulated by the similarity of brands' psychological features when different voxels were included (Figure S10).

2.8 Robustness to Excluding Visual Cortex Voxels

The most predictive voxels were distributed in the cortex, including occipital lobes (Figure 4 and Figure S6). As a robustness check, we ran the analysis excluding voxels in the occipital cortex using an ROI mask (Figure S11A), which was estimated in a general linear model with a regressor including all of the brand-viewing tasks. The mask was created using the group-average beta values across 17 subjects with the criteria of $p<0.002$ and at least 1000 contiguous voxels. We then ran the computational model for each participant excluding voxels within the mask. Specifically, we performed the same analysis but selected the 500 most stable voxels outside the mask. Our result is robust to masking for the overall hit rate and the significant relationship between hit rate and subjective similarity (Figure S11B), for the strength of neural correlation modulated by the similarity of brands' psychological features (Figure S11C), and for the significant relationship between the subjective similarity and the difference between the correlation of the predicted brain images and the actual brain images for correctly matched pair and the incorrectly matched pair (Figure S11D).

2.9 Robustness to Controlling for Physical Properties of Brand Logos

As a robustness check, we account for brain activities associated with the visual activation when viewing the brand logos, by comparing the result in three models with different sets of explaining variables. The first model is our main result, using the five factors of psychological features. In the second one, we used the other five variables obtained from the ratings of an independent population regarding to the physical properties of the brand logos, such as whether the logo is red, blue, round, whether it has hard edges, and whether it contains words (Figure S12A). In the third model, we included both sets of variables: five psychological features and five physical properties. We found that although the model of physical properties yielded a higher prediction rate compared with the psychological-feature model (68% versus 58%), the combination of psychological features and physical properties does the best (73%) (Figure S12B). Also, the hit rate is modulated by the similarity in traits only in the psychological-feature model (Figure S12C).

2.10 Regression Coefficients

To visualize the regression coefficients (c_n^v) of the five dimensions of psychological features, we regress the activation levels on the five dimensions for each voxel of the average subject. Notice that we did not hold out any data. The average regression coefficients within each of the clusters shown in Figure 4 are plotted in Figure S13-S17. The brain regions were ordered by anterior/posterior axis in clockwise fashion.

2.11 Univariate Analyses of Brand Personality Factors

We use a univariate approach to identify the brain regions significantly correlated with each of the five dimensions of brand personality, with parametric modulations in a general linear model using SPM8. The brain regions associated with each of the five factors are shown in Figure S18. Univariate analyses are typically less sensitive than multivariate analyses because the former does not consider information that is distributed among activity patterns between voxels. Consistent with this, we find only a few patches of the visual cortex that respond to brand personality factors at the $p<0.001$ level (Figure S18).

3. Figures

Figure S1: Experimental Protocol

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. In addition, there were twelve fixations lasting for 4-8 seconds and six self-paced catch questions.

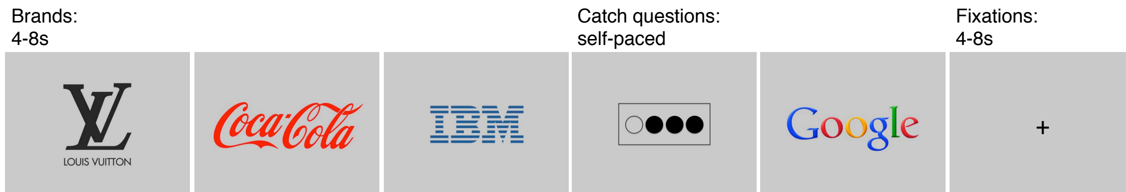


Figure S2: Factor Loadings of Traits

The factor analysis and the criteria yielded five factors, labeled as excitement, competence, sincerity, ruggedness, and sophistication. The factor loadings of traits showed that our results largely replicated those of previous studies. For example, the first factor loaded highly on the traits "trendy", "unique", and "original"—commonly referred to as the Excitement factor. The third factor, referred as Sincerity, loaded highly on traits such as "friendly", "family-oriented", and "wholesome".

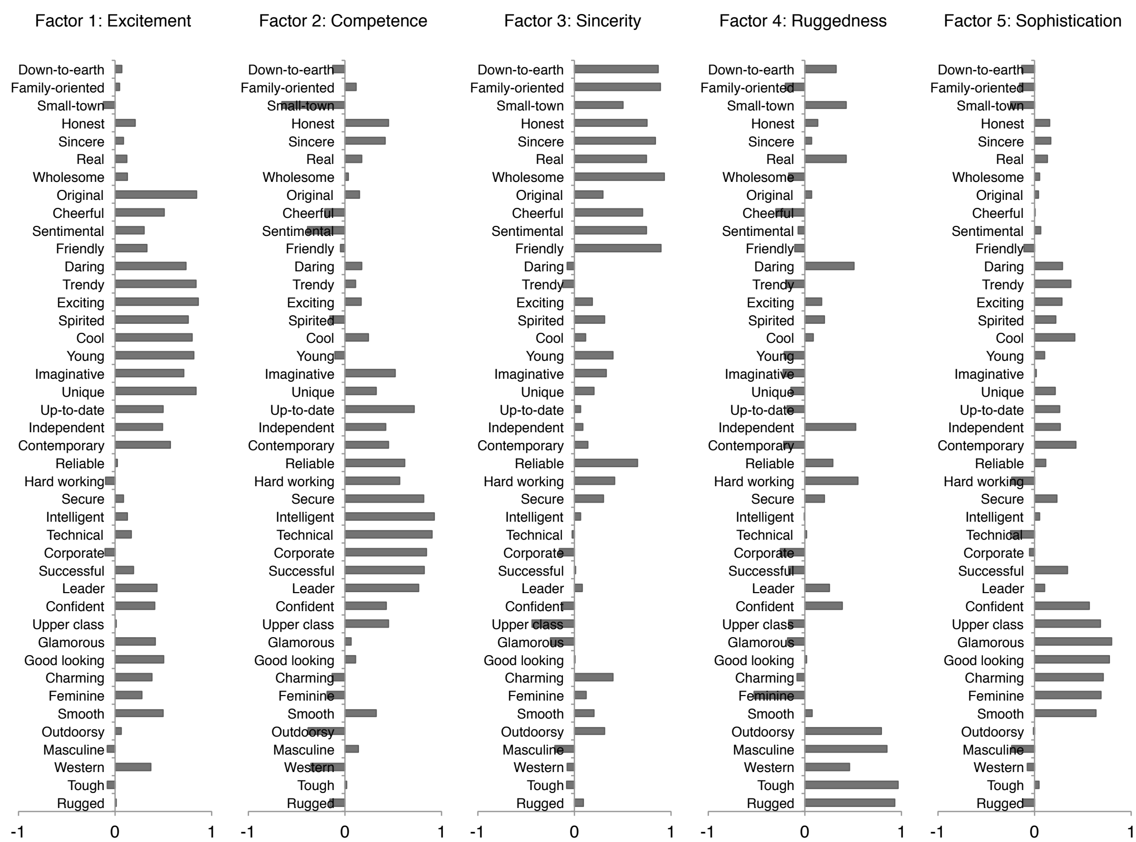


Figure S3: Radar Charts of the Factor Scores of Brands

Each brand was re-expressed in terms of its feature vector, defined as the strength of association between the brand and the personality factors. These factor scores for each brand are shown in the radar charts (Ex: excitement, Com: competence, Sin: sincerity, Rug: ruggedness, and So: sophistication). Green (Red) regions indicate positive (negative) factor scores.

Figure S4: Model Performance on the Individual Level

Average hit rate over all of the possible combination of hold-out data for each subject. Error bars represent 95% confidence intervals. Subjects were sorted by the performance of the model.

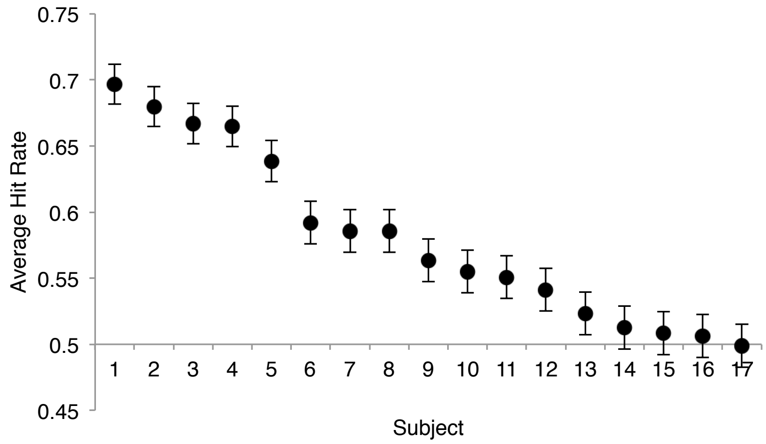


Figure S5: Correlation between Neural Similarity and Psychological Similarity.

Separating the brands based on subjective similarity into quartiles, we find a significant relationship between the subjective similarity and the difference between the correlation of the predicted brain images and the actual brain images for correctly matched pair (dark arrow in Figure 2D) and the incorrectly matched pair (light arrow in Figure 2D). That is, the difference in correlation between the matched brain images and the mismatched brain images is larger when brands are more dissimilar. When brands are highly similar (mean Pearson r=0.75), there is no significant difference between the correlation of matched images and the correlation of mismatched images. Errorbars indicate SEM.

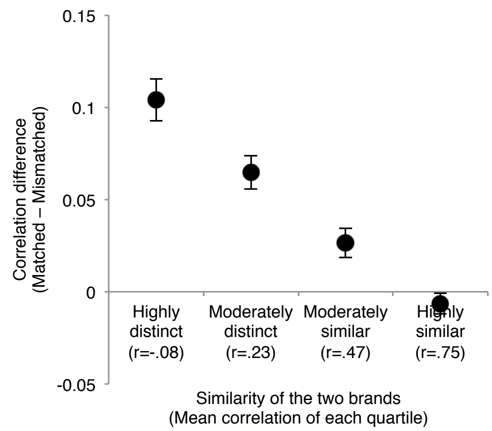


Figure S6: Accuracy Map

Surface rendering (top) and the glass brain (bottom) of locations of the most accurately predicted voxels, i.e., voxels with highest correlation between predicted 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. These voxel clusters are distributed throughout the cortex and located in the left and right occipital and frontal lobes (Table 1). Note that decoding results were robust to exclusion of visual cortices.

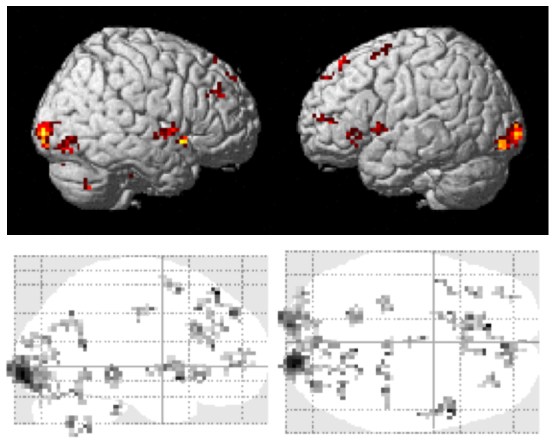


Figure S7: Robustness to Extracting Representative fMRI Response to the Brands

Our result is robust to different ways of extracting the representative of neural responses to brands. We are able to predict significantly better than chance which brand the participant was thinking about using the brain activities estimated (1) with impulse function in the LS-S model, (2) with the full duration in the LS-S model, and (3) with the standard one GLM model. **(A)** Consistent with Mumford et al. 2012, the prediction rates of the alternative models are somewhat worse than using the duration 0 LS-S model, but remain quite significant ($p<0.005$, Figure S7A). **(B)** The prediction rates modulated by psychological similarity remain qualitatively unchanged (Figure S7B).

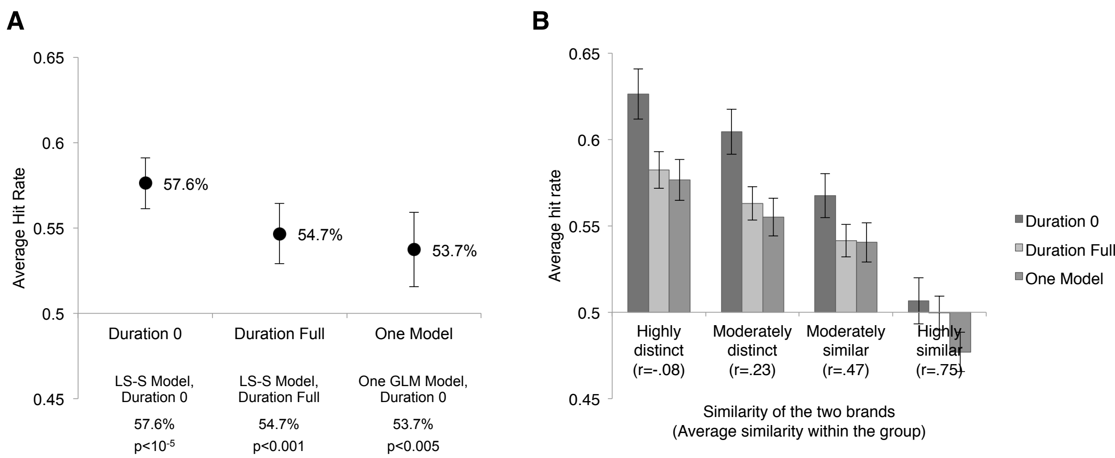


Figure S8: Robustness to the Measure of Psychological Similarity of Brands

(A) The difference in correlation between the matched brain images and the mismatched brain images is larger when brands are more dissimilar, measured as the larger Euclidean distance between the two brands' feature vectors. **(B)** We plotted, for each brand pair, the correlation between predicted and observed brand image (y-axis) against similarity in brand meaning as measured using Euclidean distance of factor scores (x-axis). We found that strength of neural correlation is robustly modulated by the similarity of brands' latent properties ($r = -0.56, p < 10^{-7}$). **(C)** Separating the brands based on subjective similarity into quartiles as assessed based on Euclidean distance of factor scores, we find a significant relationship between hit rate and subjective similarity.

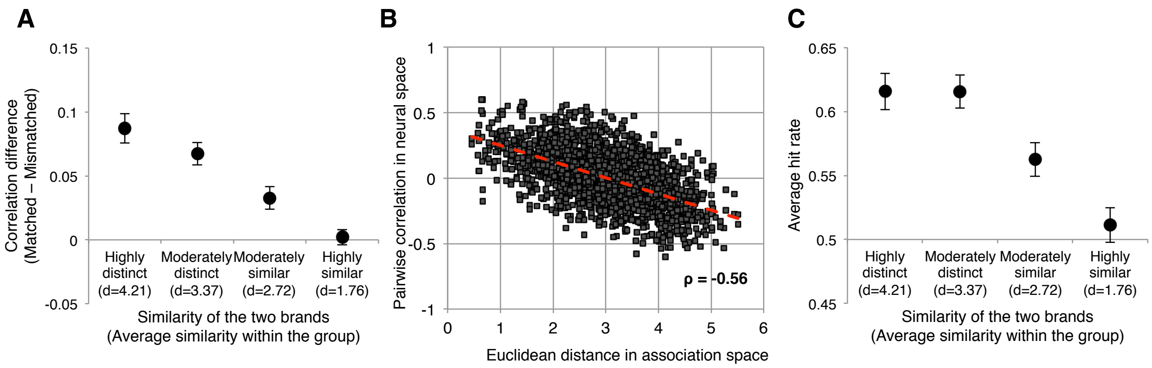


Figure S9: Robustness to Number of Voxels (Hit Rate)

The overall hit rate for hold-out classification was 58% when comparing the predicted and observed brain images using the 500 most stable voxels. When more voxels were included in the comparison, our result was still robust. 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 when different number of voxels were included.

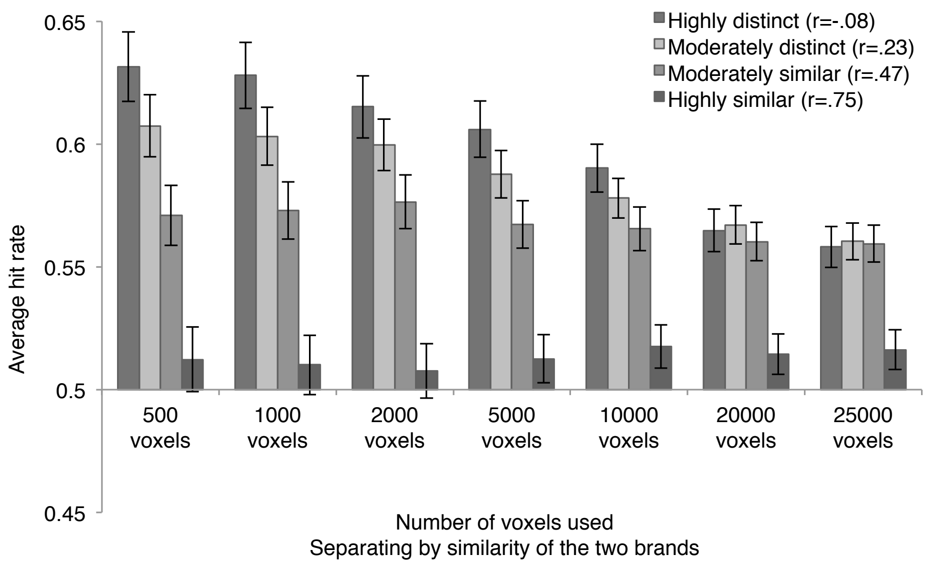


Figure S10: Robustness to Number of Voxels (Correlation)

To compare similarity between neural and psychological measures of brand associations, we plotted, for each brand pair, the correlation between predicted and observed brain images (y-axis) against similarity in brand meaning as measured using correlation of trait ratings (x-axis). The correlation between the predicted and the observed brain images was calculated using **(A)** 500 **(B)** 1000 **(C)** 5000, and **(D)** 25000 most stable voxels. We found that strength of neural correlation is robustly modulated by the similarity of brands' latent properties when different voxels were included.

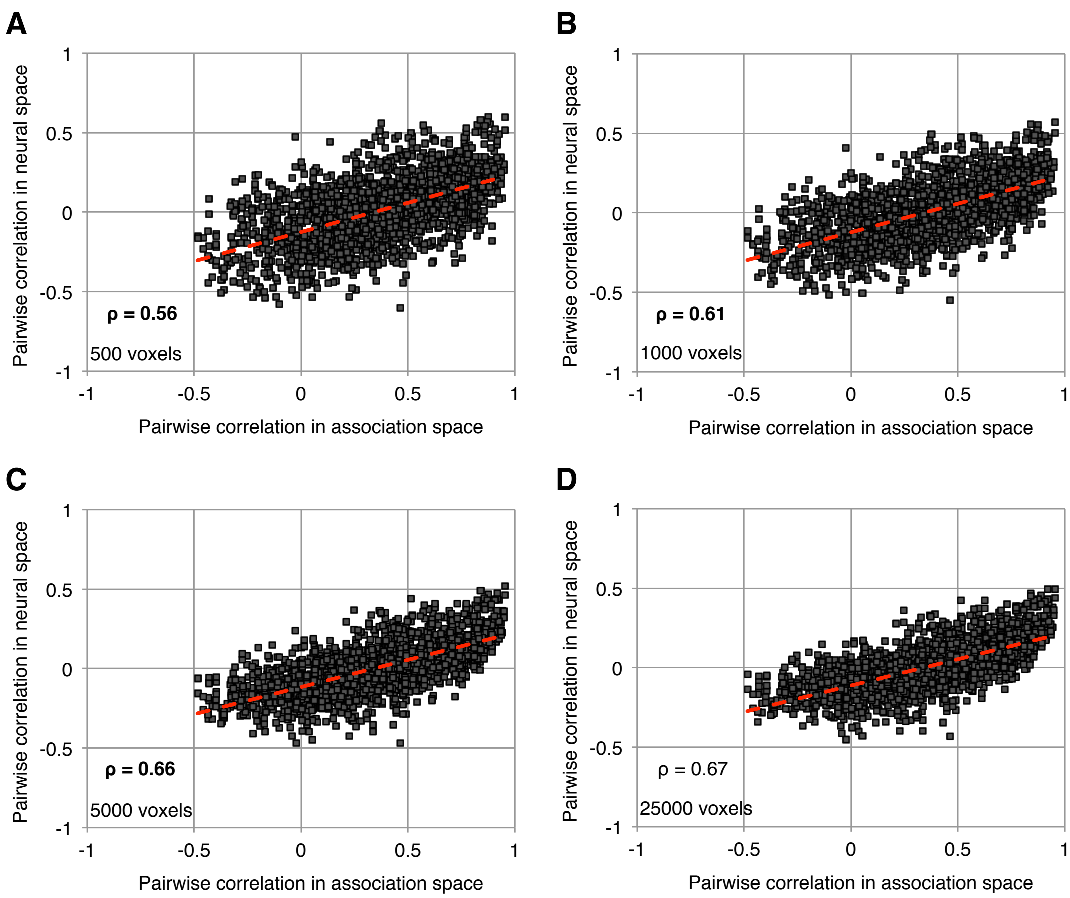


Figure S11: Robustness to Excluding Visual Cortex Voxels

We ran the analysis excluding voxels in the occipital cortex as a robustness check of the result. **(A)** The ROI mask used to exclude voxels within occipital lobes. **(B)** The overall hit rate was significantly better than chance, and the significant relationship between hit rate and subjective similarity was robust to masking. **(C)** The strength of neural correlation modulated by the similarity of brands' personality properties was robust to masking. **(D)** The significant relationship between the subjective similarity and the difference between the correlation of the predicted brain images and the actual brain images for correctly matched pair and the incorrectly matched pair was robust to masking.

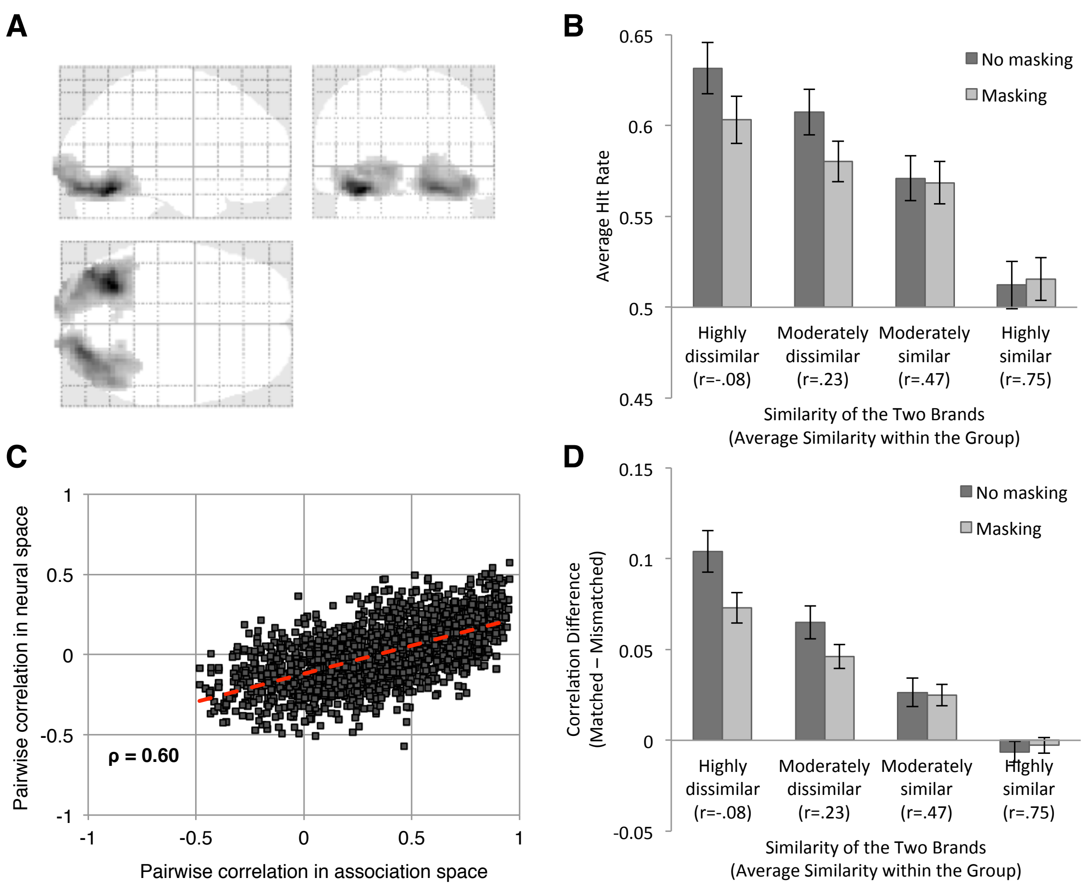


Figure S12: Robustness to Controlling for Physical Properties of Brand Logos

We compared the result in three models with different sets of explaining variables to account for brain activities associated with the visual activation. **(A)** Variables used in the models. **(B)** Although the model of physical properties yields a higher prediction rate compared with the psychological association model, the combination of factors and physical properties does the best. **(C)** The hit rate is modulated by the similarity in traits only in the psychological association model.

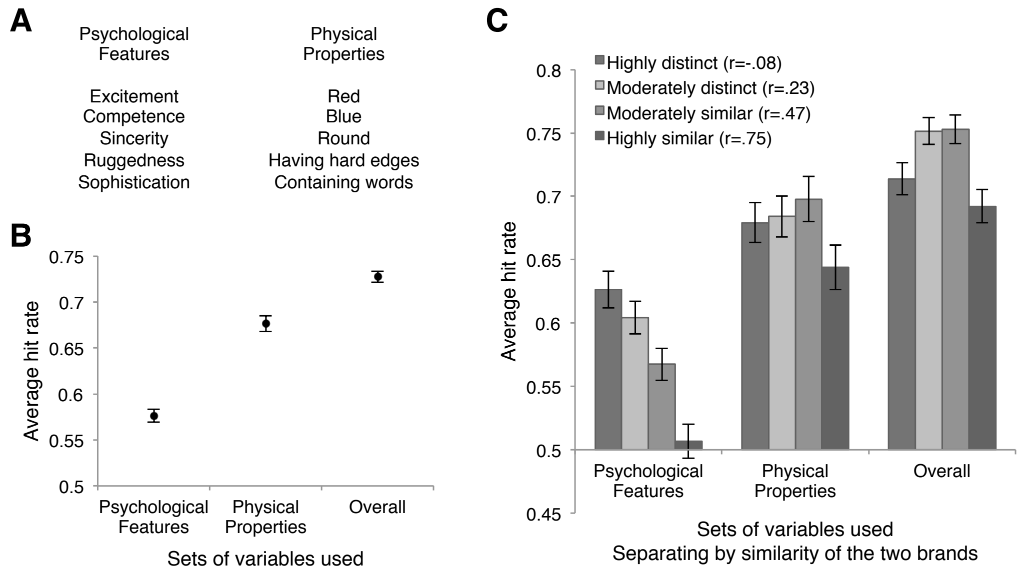


Figure S13: Average Regression Coefficients of Excitement

The average regression coefficients of excitement within each cluster in Figure 4 are shown in the figure, with the coordinate of the peak voxel in the parentheses.

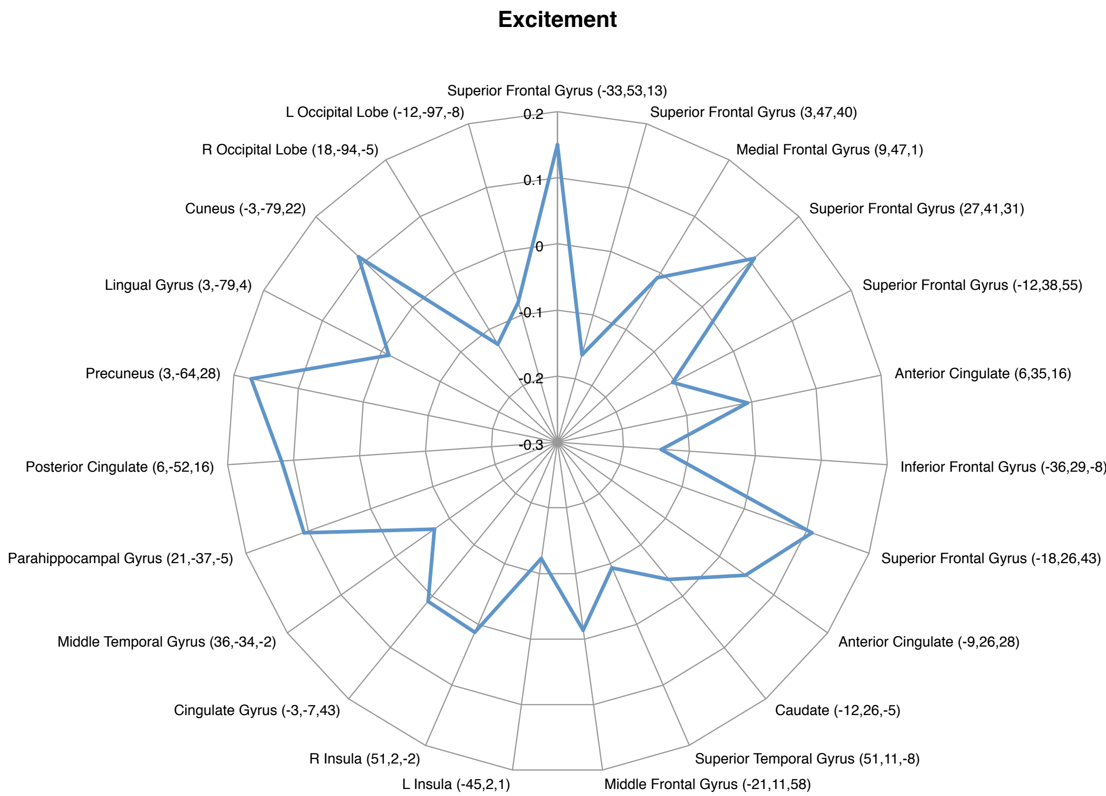


Figure S14: Average Regression Coefficients of Competence

The average regression coefficients of competence within each cluster in Figure 4 are shown in the figure, with the coordinate of the peak voxel in the parentheses.

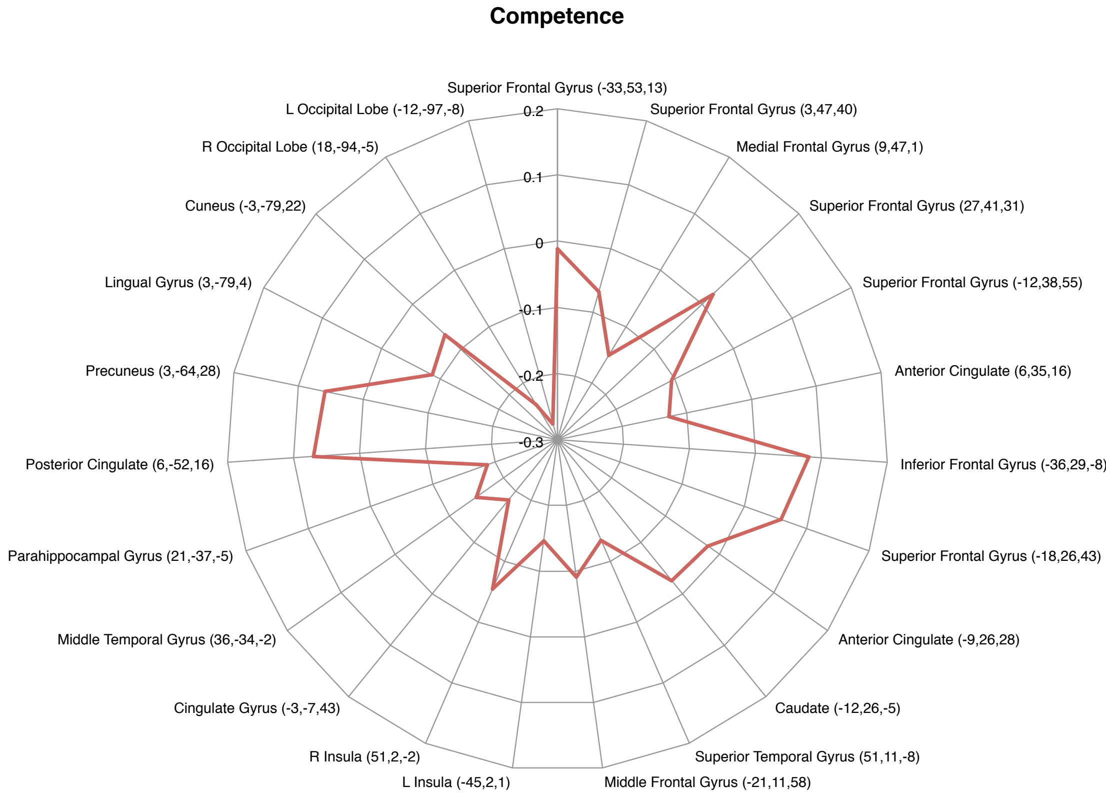


Figure S15: Average Regression Coefficients of Sincerity

The average regression coefficients of sincerity within each cluster in Figure 4 are shown in the figure, with the coordinate of the peak voxel in the parentheses.

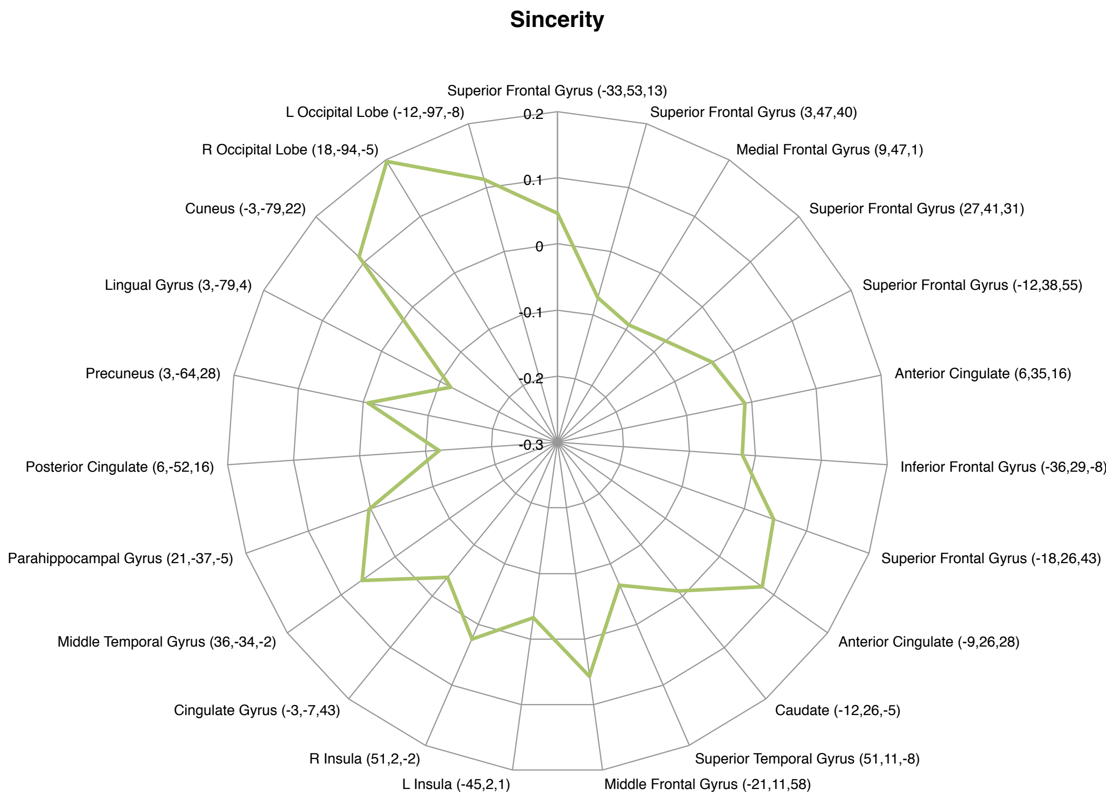


Figure S16: Average Regression Coefficients of Ruggedness

The average regression coefficients of ruggedness within each cluster in Figure 4 are shown in the figure, with the coordinate of the peak voxel in the parentheses.

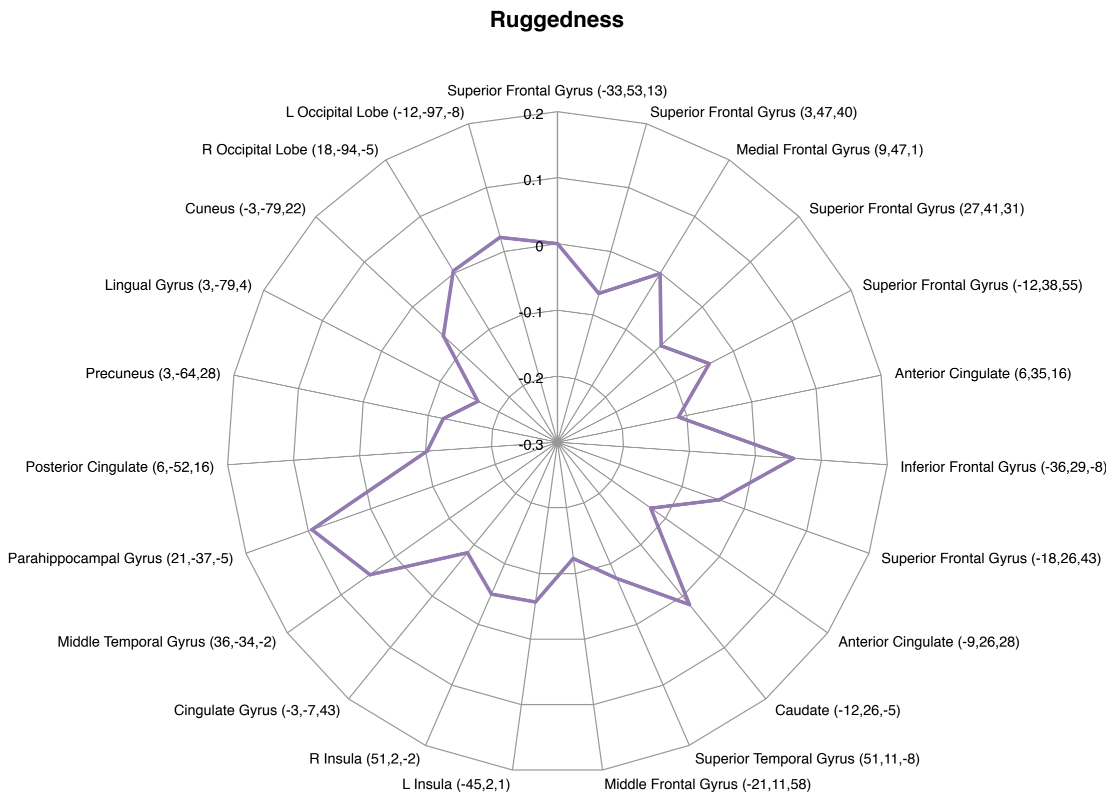


Figure S17: Average Regression Coefficients of Sophistication

The average regression coefficients of sophistication within each cluster in Figure 4 are shown in the figure, with the coordinate of the peak voxel in the parentheses.

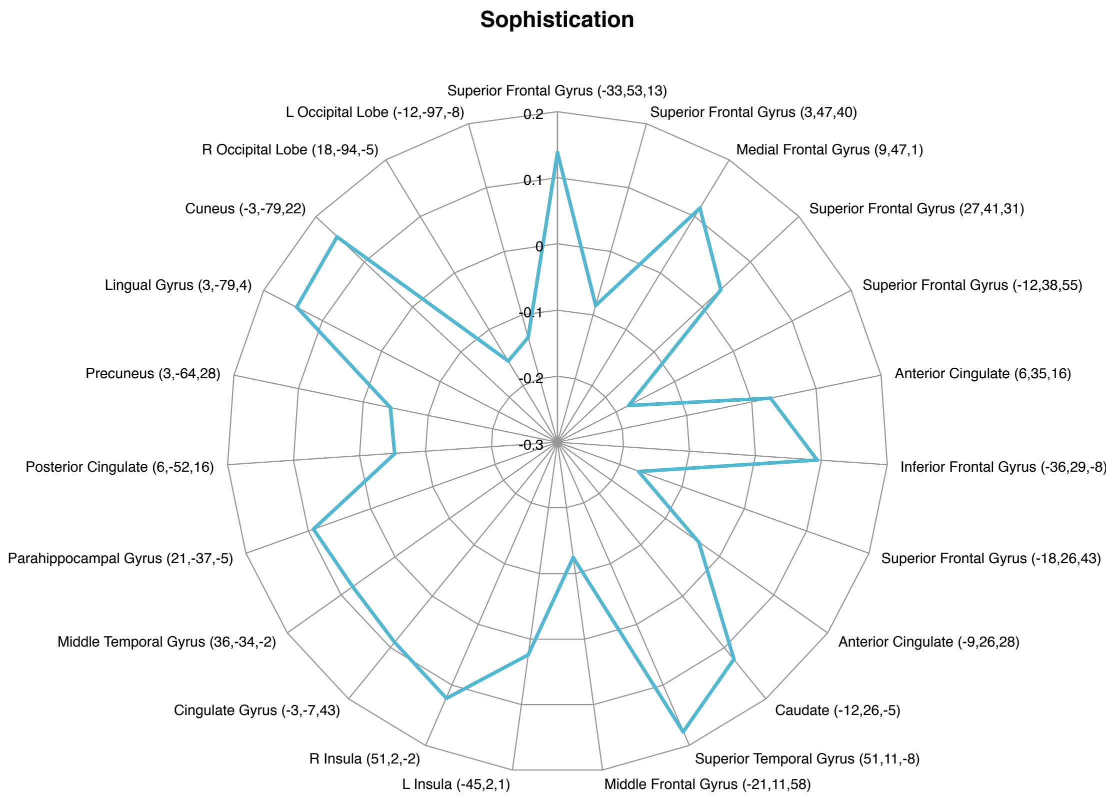
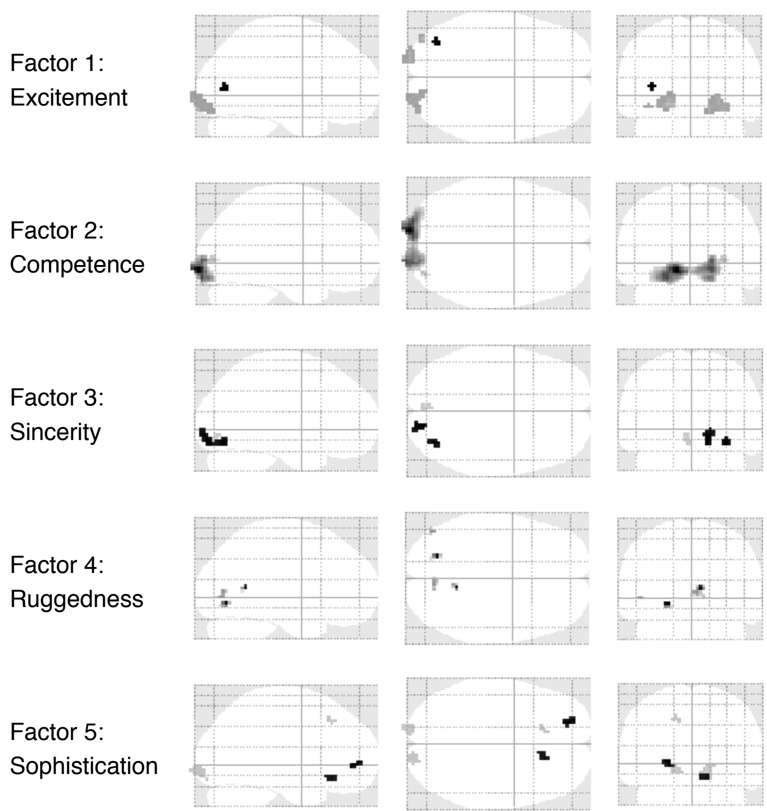


Figure S18: Univariate Analyses of Brand Personality Factors

Unlike our decoding analysis, univariate analyses are typically less sensitive than multivariate analyses because the former does not consider information that is distributed among activity patterns between voxels. Consistent with this, we find only a few patches of the visual cortex that respond to brand personality factors at the p<0.001 level.



4. Tables

Table S1: Traits Used in the Survey

After the scanning session, participants were asked to complete a survey about the brands the saw in the scanner. For each brand, participant rated the descriptiveness of 42 traits, with a five-point scale from not at all descriptive to extremely descriptive.

Dimension	Sincerity	Excitement	Competence	Sophistication	Ruggedness
Traits	Down-to-earth Family oriented Small-town Honest Sincere Real Wholesome Original Cheerful Sentimental Friendly	Daring Trendy Exciting Spirited Cool Young Imaginative Unique Up-to-date Independent Contemporary	Reliable Hard-working Secure Intelligent Technical Corporate Successful Leader Confident	Upper-class Glamorous Good-looking Charming Feminine Smooth	Outdoorsy Masculine Western Tough Rugged

Table S2: Dimensions of Brand Characteristics

Summary of the five factors obtained from the factor analysis.

Name	Dimension	Variance Explained	Eigenvalue	Traits with highest item-to-total correlations
Excitement	1	35.0%	14.69	Exciting, Original, Unique, Trendy, Young.
Competence	2	19.1%	8.03	Intelligent, Technical, Corporate, Successful, Secure.
Sincerity	3	14.8%	6.22	Wholesome, Friendly, Family-oriented, Down-to-earth, Sincere.
Ruggedness	4	12.3%	5.19	Tough, Rugged, Masculine.
Sophistication	5	4.7%	1.96	Glamorous, Good-looking, Charming.

Table S3: Factor Scores of the Brands Used in the Experiment

Brand	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Amazon.com	0.924	1.282	0.638	0.083	0.101
American Express	-1.177	0.452	-0.898	-0.480	0.444
Apple	1.695	1.208	0.126	0.073	0.435
BMW	0.257	0.937	-0.696	0.683	1.467
Budweiser	-0.597	-1.998	-0.382	0.907	-1.168
Campbell’s	-1.175	-1.082	2.061	-0.139	0.011
Canon	0.195	1.082	0.532	0.050	-0.121
Cisco	-0.787	0.975	-0.397	-0.050	-0.780
Coca-Cola	0.339	-0.719	0.757	-0.265	0.170
Dell	-0.880	0.902	0.072	-0.140	-0.458
Disney	1.427	-0.277	1.634	-1.060	-0.330
Ford	-0.370	-0.739	0.432	1.678	-0.441
GE	-1.315	0.919	0.494	0.123	-0.200
Gillette	-0.849	0.033	0.131	1.377	0.887
Goldman Sachs	-1.343	0.025	-2.272	-0.247	-0.172
Google	1.980	1.505	0.339	0.141	-0.604
Gucci	0.662	-0.465	-1.383	-0.953	2.175
H&M	0.732	-1.124	-0.377	-1.069	0.329
Harley-Davidson	1.529	-0.835	-0.878	2.703	-0.455
HP	-0.564	0.678	-0.328	-0.715	-0.884
Honda	-0.104	0.384	0.918	0.434	0.467
IBM	-0.526	1.761	-0.515	-0.038	-1.089
IKEA	0.740	-0.112	1.114	-0.741	0.048
Intel	-0.356	1.699	-0.201	-0.143	-0.829
J.P. Morgan	-1.775	0.436	-1.609	-0.186	0.137
Jack Daniel’s	-0.077	-1.363	-0.533	1.604	0.194
Kellogg's	-0.914	-0.701	1.954	-0.574	0.170
L’Oréal	0.199	-0.718	-0.388	-1.229	1.455
Lancôme	-0.565	-1.090	-0.363	-1.534	2.325
Levi's	-0.150	-0.967	1.544	2.064	0.876
Louis Vuitton	0.646	-0.099	-1.517	-0.815	1.681
Marlboro	-0.587	-1.749	-1.655	1.350	-1.509
McDonald's	-0.576	-1.414	-0.837	-1.526	-2.114
Mercedes-Benz	-0.496	0.881	-0.339	0.585	2.072
Microsoft	-0.474	1.070	-0.263	-0.429	-1.169
MTV	2.534	-1.146	-1.187	-0.638	-0.879
Nestlé	-0.724	-1.217	1.757	-1.428	0.193
Nike	1.554	0.268	0.139	1.772	0.635
Nintendo	1.347	0.023	0.104	-1.207	-1.629
Pepsi	0.277	-0.781	0.395	-0.298	-0.292
Sony	0.517	1.160	-0.330	0.164	-0.136
Toyota	-0.527	0.288	0.884	-0.024	0.282
UPS	-1.233	0.769	1.126	0.851	-0.271
Yahoo!	0.586	-0.142	0.195	-0.715	-1.026

5. Reference

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