Neural profiling of brands: Mapping brand image in consumers' brains with visual templates

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ABSTRACT

We demonstrate a novel template-based approach to profiling brand image using functional magnetic resonance imaging (fMRI). By comparing consumers' brain responses during passive viewing of visual templates (photos depicting various social scenarios) and brain responses during active visualizing of a brand's image, we generate individual neural profiles of brand image that correlate with the participant's own self-report perception of those consumer brands. In aggregate, these neural profiles of brand image are associated with perceived co-branding suitability and reflect brand image strength rated by a separate and bigger sample of consumers. This neural profiling approach offers a customizable tool for inspecting and comparing brand-specific mental associations, both across brands and across consumers. It also demonstrates the potential of using pattern analysis of neuroimaging data to study multi-sensory, nonverbal consumer knowledge and experience.

Keywords: consumer neuroscience, brand image, brand equity, functional magnetic resonance imaging, pattern analysis

INTRODUCTION

Communicating a brand's image clearly and effectively to consumers is crucial for building brand equity (Keller 1993, 2001; Park, Jaworski, and Maclnnis 1986). Although brand image as a construct is nebulous and hard to define, it is generally understood as a broad set of mental associations consumers have in relation to a brand, either through exposure to marketing or through prior interactions with the brand, during and after purchase (Aaker 1991; Brakus, Schmitt, and Zarantonello 2009; Herzog 1963; Keller 1993). Marketing researchers have stressed the importance of understanding how consumers form, organize and access these mental associations with brands (Alba and Hutchinson 1987; Zaltman and Coulter 1995).

Instilling these mental associations with a brand in the consumer's mind is often achieved by deliberate marketing. In Keller's (2001) formulation of brand-building, brand imagery involves 'a fairly concrete initial articulation of user and usage imagery that, over time, leads to broader, more abstract brand association of personality' (p. 24). Such user and usage imagery fleshes out a situated moment that epitomizes the brand's desired and desirable image. For example, a cereal commercial on TV may feature a loving family around the breakfast table; a beer ad may depict a trendy partying crowd consuming the beverage. While these marketing efforts aim at reinforcing the associations between the brand and its desired user and usage imagery, how strongly and consistently these associations are forged in consumers' minds – and thus how effective such advertising is – is hard to quantify and measure with self-report instruments.

In this paper we propose using a neuroimaging technique, namely functional magnetic resonance imaging (fMRI), to extract knowledge of brand image from consumers' brains through the process of visualization. Visualization is defined here as the conscious process of creating a visual representation for a brand, which consists of not only perceptual associations (visual features, images and scenes), but also cognitive (intended user and usage) and affective (feelings and mood) information. We aimed at building neural profiles of brand image by comparing brain activation patterns during active visualization of brand image to those during passive viewing of a large set of naturalistic pictures as visual templates. This approach has the potential advantage of circumventing verbal articulation of what is essentially a visual experience.

Beyond Self-Report: Extracting Brand Information from the Consumer's Brain

There are existing self-report instruments that can be used to evaluate the transmission of brand image from marketing activities to the collective mind of consumers (Brakus, Schmitt, and Zarantonello 2009; Fournier 1998; John et al. 2006; Krishnan 1996; Low and Lamb 2000; Roth 1994). One of the most commonly used self-report instruments is the brand personality questionnaire (Aaker 1997), which provides a quick diagnostic of brand image based on a predefined set of personality attributes and has the advantage of being convenient to administer to a large group of consumers. Qualitative techniques, such as imagery elicitation (Roth 1994), structured interviews (Fournier 1998), laddering (Reynolds and Gutman 1988), and the Zaltman Metaphor Elicitation Technique (Coulter and Zaltman 1994), offer rich content for marketing insight based on individual in-depth reports. In between standardized diagnostics and qualitative reports are methodologies developed specifically for visualizing the mental association network, such as free association (Krishnan 1996) and concept mapping (John et al. 2006). Most of these self-report measures rely on translating one's mental associations into verbal description. Turning feelings and sensations into words inevitably requires a certain level of abstraction and simplification, and may result in both loss of information and introduction of response artifacts in the process. This is especially pertinent in the context of brand communication, where much marketing activities take place in sensory pathways: visual, auditory, olfactory and tactile (Krishna 2012; Krishna and Schwarz 2014). In fact, the term ‘brand image’ implies its predominantly visual nature, which is often transmitted through video and print advertisements. Asking consumers to verbalize their visual knowledge of brands entails a trade-off between manageability and depth; marketing researchers either rely on a set of predefined labels for quick comparisons, or obtain insights from in-depth qualitative reports.

The use of neuroscientific methods in marketing studies promises new ways to gain access to consumers’ minds without potential bias and limitation in self-report (Plassmann et al. 2015). In previous work on the neuroscience of branding, a number of studies have uncovered brain areas which exhibit differential reactions to brands with varying characteristics, such as familiarity, preference and perceived status (see Plassmann, Ramsøy, and Milosavljevic 2012 for a comprehensive review). For example, a study comparing brain activations of brand and person judgments found that brand judgment involved particularly the left inferior prefrontal cortex, an area known to be involved in object processing, suggesting that brands may be perceived more like objects than persons (Yoon et al. 2006). Brand familiarity is linked to memory-related neural pathways in hippocampus, frontal and temporal lobes (Esch et al. 2012; Klucharev, Smidts, and Fernández 2008), while interacting with preferred brands or luxury brands is associated with stronger activations in ventromedial prefrontal cortex and striatum, brain areas known for their role in reward processing (McClure et al. 2004; Plassmann et al. 2008; Schaefer and Rotte 2007). In sum, these studies provide good evidence that consumer knowledge of brands is in some way reliably represented by activity changes in particular brain areas. However, the most common analysis paradigm in the current literature involves categorical comparisons (e.g., familiar vs unfamiliar brands), which are binary in nature and thus do not differentiate individual brands. Moreover, these studies are chiefly concerned with identifying anatomical regions in the brain associated with brand information processing, thus shedding light on the neural mechanism of such mental processes. However, exactly *what* brand information is represented in the brain, is little studied. For example, are brands such as Disney and Apple, both widely known but with highly distinct images, uniquely represented in the brain? Moreover, do these differences in neural responses between brands, and across individuals, tell us about how these brands are perceived?

Decoding Brand Image Based on Existing Brand Knowledge

Recently, Chen, Nelson and Hsu (2015) attempted to map neural response patterns onto multidimensional information of brand image. They started from the assumption that brands have a well-defined set of attributes uniformly perceived by consumers, thus forming the basis of their decoding model. Neural responses during passive viewing of a set of 44 well-known brands were first obtained. Selecting Aaker's (1997) brand personality as the guiding model, which organizes brand information into five dimensions, the researchers were then able to fit existing brand personality profiles into a regression model described by a distributed network of brain activations. Specifically, they modeled the personality factor scores of 42 brands (training set) with brain responses during passive viewing of brand logos, and then used the brain model to predict the personality factor scores of two remaining brands (testing set). By assuming the existence of a 'ground truth' (i.e., brands have well-defined and universal personality profiles that exist independently outside consumer's mind), the study demonstrated that this model-based approach can be useful in extracting brand information of an unknown brand from brain activities based on an external set of well-defined brands.

Neural decoding using existing knowledge of brands, while being an invaluable addition to the marketer's toolbox, requires the assumption that brand perception is uniform across consumers. This might be problematic if some brands in the training sample change their personalities over time due to either endogenous (brand re-positioning) or exogenous (change of market trends) forces; or when the testing population comes from a different demographic segment or culture than the training population, and therefore may not share the same perceptions of brands.

In this paper, we demonstrate an alternative approach to inferring mental content in consumers' brains by applying pattern analysis on neuroimaging data. We refer to this as template-based profiling: instead of decoding brand image in consumers' brains with *a priori* knowledge of well-known brands, mental content is inferred by comparing neural responses evoked by brands to those evoked by a large set of naturalistic pictures as visual templates (see Figure 1 for a schematic representation of the two approaches). There are two main assumptions behind the current effort: that (a) unique mental associations with brands can be represented by mental visualization, and that (b) mental images elicited during visualization are processed at least partly through the same neural pathways involved in viewing actual pictures. The first assumption rests on the fact that advertising is in most part communicated visually (Babin and Burns 1997; Henderson et al. 2003; Kirmani and Zeithaml 1993; LaBarbera, Weingard, and Yorkston 1998). It is therefore reasonable to assume that consumers form their brand knowledge through exposure to visual elements, and that they should be able to retrieve such knowledge via active visual reconstruction of brand image. The second assumption finds empirical support in a number of neuroscientific studies which show considerable overlap in activated brain areas during visual perception and visual imagery (Chen et al. 1998; Kosslyn, Ganis, and Thompson

2001; Kosslyn and Thompson 2003; Roland and Gulyás 1994). Furthermore, neural representations evoked in visual perception and in visual imagery appear to share common features (Cichy, Heinzle, and Haynes 2012; O'Craven and Kanwisher 2000; Slotnick, Thompson, and Kosslyn 2005). For example, Horikawa and associates (2013) reported they were able to decode neural activity associated with visual imagery during sleep (i.e., dreams) by comparing these neural responses to those elicited by the viewing of various images during wakefulness.

STUDY 1: BUILDING INDIVIDUAL NEURAL PROFILES OF BRAND IMAGE

Overview of the Profiling Approach

The aim of Study 1 is to extract neural responses that represent an individual's knowledge of brands, and then validate our findings by comparing them with the self-report brand perception of the individual. Specifically, we first asked participants to engage in a visualization exercise involving brands, in which they tried to construct a mental picture that, in their opinion, best fit the brand's intended user and usage imagery and captured the 'essence' of the brand image. We recorded neural activities as they formed those brand visual imageries in their mind (brand-imagery neural patterns). In the next step, participants viewed a series of naturalistic pictures depicting different social scenarios while their neural activities were recorded (picture-viewing neural patterns). The idea is to essentially describe a brand's image in terms of its resemblance to various social scenarios, manifested in the participant's brain as similarities between brand-imagery neural patterns and picture-viewing neural patterns. In effect, the pictures depicting social scenarios collectively form a profiling space, based on which the content of brand image is inferred.

Determining the profiling space. Instead of selecting well-known brands as a training set as in Chen, Nelson and Hsu (2015), the current approach requires a collection of templates that would serve as a profiling space. In this study we chose social context, based on the observation that many advertisements showcase consumption in a social setting. For example, an analysis of 1,279 print advertisements from eight countries found that 26-52% of them depicted more than one person (Cutler, Erdem, and Javalgi 1997). We further selected four contexts – familial, intimate, communal and professional – that we believed would capture the different dimensions of social relationships according to sociological literature: kin versus non-kin, sexual-romantic versus non-sexual-romantic, cohabiting versus noncohabiting, hierarchical versus egalitarian (Blumstein and Kollock 1988). It is important to note that our choice of the social context images was not an attempt to comprehensively describe all aspects of brand image; rather, we believe the four social contexts provide an adequate profiling space that would be able to explain enough variance in the visual imageries participants would generate. In a supplementary analysis, we found supporting evidence that among a large set of consumer brands, consumers did report user and usage imageries that fit those four contexts, and these contexts could be used to differentiate brands (see Supplementary Analysis [S.A.] 1 in the web appendix).

Validating the model. To verify if this approach did indeed extract neural information of the individual's own brand knowledge, we considered two aspects: content and similarity (see Figure 3B, upper panel for an overview). First, neural information extracted from the individual should be able to tell us how the individual thought about a particular brand. In the current study, we used visual templates from four different social contexts; for validation, we asked participants to rate the brands according to the same four categories. Thus our first proposition was:

H_1: Brand-imagery neural patterns correspond with the individual's self-report perception of the brand's image.

In addition to content, we should be able to make use of neural information to map out an individual's perception of brand similarity. Specifically, we adapted the paradigm used by Charest and colleagues (2014) and tested if there was correspondence between neural and self-report brand similarity. To do so, we first obtained a neural measure of brand similarity by (a) creating a 'neural profile' for each brand by comparing the brand-evoked neural pattern to each of the picture-induced neural patterns; and then (b) measuring the similarity of neural profiles from different brands within an individual. We therefore tested the following hypothesis:

H_2: Brands that elicit similar neural profiles within an individual are perceived to be similar by that individual.

Method

Fourteen well-known brands (see web appendix) with diverse brand images were selected from different product categories (electronics, apparel, personal care products, software), such that brands in the same product category could have different images (e.g., Dell and Apple), while brands in different product categories could have a similar image (e.g., Axe and Durex).

As visual templates, we used 112 pictures of naturalistic scenarios depicting various everyday situations, obtained from the internet (see web appendix for examples; the whole set of pictures are available upon request). All of the pictures had neutral to positive valence as we focused on positive brand images for the purpose of this study. These pictures fell into four social contexts (28 pictures each), showing professionally-dressed people working in office settings (professional), intimate moments with romantic partner (intimate), family gatherings (familial), and partying with friends (communal).

We recruited 38 students (21 men, age range = 18-35, mean = 23.3, SD = 3.5) via the recruitment system of the university. They received a fixed payment of €25 for their participation. One participant's data were excluded from analysis due to excessive head movements (> 3mm) while in the scanner, leaving 37 participants in the analysis. The study was approved by the local ethics committee, in line with the Declaration of Helsinki. All participants signed informed consent prior to participation, and then were given time (before entering the scanner) to construct mental images for each of the brands. Inside the scanner, they completed two tasks (see web appendix for magnetic resonance data acquisition parameters), after which they performed a brand similarity judgment task outside scanner. About one week later, they completed an online questionnaire on brand perception and co-branding evaluation.

Visual imagery formation prior to scanning. To evoke their visual imagery, participants were asked to read an instruction booklet containing the 14 brands. For each of these brands, participants reflected on its intended image and message, and constructed a mental image depicting a typical social context associated with it (see web appendix for the instructions). Importantly, participants were completely free in the image they constructed; that is, they were not provided cues in any way to form any particular image.

To make sure participants understood the instructions, they first completed a practice brand (a well-known supermarket chain) in the presence of the experimenter, who answered questions participants might have. The practice brand would not appear in the scanner task later. Afterwards, they continued with the 14 brands at their own pace without time limit nor interaction with the experimenter. The process took about 30-45 minutes. Once completed, participants were asked to practice in silence, for each brand, repeatedly reconstructing the images in their mind as vividly as possible, until they reported being able to recall all brands' images with ease. Although the participants were asked in the booklet to describe the mental images in writing, the answers they gave were not analyzed in this study (examples are included in the web appendix).

Scanner tasks. There were two tasks that took place inside the scanner, separated by the acquisition of the structural (anatomical) scan (Figure 2A). The first task was brand imagery elicitation ('brand imagery' task), and the second task was the viewing of pictures depicting various social contexts ('picture viewing' task).

During the brand imagery task, participants were asked to recall the mental images they had constructed. Each trial began with a fixation cross, after which a brand logo was shown for 2s, followed by a recall cue (2s), a period in which subjects recalled the brand image (7s), and an end cue (1s). Between trials there was a blank screen of jittered length (1-3s). Within one block, the 14 brand logos were displayed in random order. The task consisted of six blocks separated by breaks (10s), and lasted about 22 minutes in total. In effect, each brand appeared six times.

During the picture viewing task, participants were asked to imagine themselves being in the settings depicted by the 112 pictures. Participants did not see the pictures nor knew the picture categories in advance. On each trial, a fixation cross (1s) was followed by a cue (2s), the picture (7s) and an end cue (1s). Between trials there was a blank screen of jittered length (1-3s). The 112 pictures were grouped in four blocks of 28 pictures (seven from each category), displayed in randomized order. The four blocks were separated by short breaks (10s). The task lasted about 27 minutes in total. In effect, each picture appeared only once.

Brand similarity. Immediately after scanning, participants evaluated similarities between brands in terms of brand image. This was done by the multi-arrangement task (Kriegeskorte and Mur 2012), which is a more efficient alternative to pairwise comparisons. In this task, participants were asked to arrange the brands according to their similarity on a computer screen using drag-and-drop mouse operations, with similar brands placed closer together while dissimilar brands further from each other. (Figure 2B shows an example screenshot during the task.) Participants were explicitly asked to judge similarity solely based on brand image, instead of other criteria such as product category, perceived quality, et cetera. The process began with the total set of 14 brands and subsequently repeated with subsets of brands adaptively selected at each round, until a time limit was reached or the brand dissimilarity matrix was sufficiently stable. In a pilot test, we found that 15 minutes was sufficient time for this task of 14 brands. (For comparison, Mur et al (2013) reported that it took typically 1h for participants to arrange 95 objects.) Using this method, each participant produced a 14 × 14 dissimilarity matrix, with each matrix element denoting the relative distance between a pair of two brands (the diagonal elements are always zeros).

Brand perception. About one week later, participants filled out an online questionnaire, in which they rated, for each of the 14 brands, how closely the brand fitted each of the four words: ‘work’, ‘lust’, ‘family’, and ‘party’, respectively. Under each word there was an unmarked visual analog scale (VAS) (range: -50 – +50) with labels ‘not fitting at all’ and ‘a perfect fit’ at opposing ends. The default position of the slider was set at mid-point, and participants were required to move each slider at least once to indicate their response.

Neuroimaging Data Analysis

The neuroimaging data were first preprocessed detailed in the web appendix. The overall approach of the analysis is as follows (see Figure 3A for an overview):

Voxel selection. To find voxels sensitive to social context across participants, we created for each subject a general linear model using picture categories as box-car regressors to model neural responses during the seven seconds of picture viewing. Three regressors of non-interest (average white matter signal, average background signal, and screen luminance) were added to the model, together with a constant. Six contrasts, based on pairwise comparisons of the four social contexts, were created. These individual contrasts were entered into a random effects group-level analysis. From each group-level contrast we selected top 1% voxels in each direction (i.e., voxels with contrast values below the 1st percentile or above the 99th percentile), and then the selected voxels from all six group-level contrasts were superimposed to form our region of interest (ROI) mask for data extraction for all participants. (Varying the threshold to 0.5% or 2.5% did not materially affect the results; see S.A. 3.)

Data extraction. Within each participant, we extracted the preprocessed neural data from both brand imagery and picture viewing tasks using the ROI mask. Linear detrending, regressing out average white matter and background signal, and voxel-wise *z*-scoring were performed within each task's data. For the picture viewing data, two consecutive volumes closest to the pictures' onset time (0s and 2.3s, adding 6s to account for the hemodynamic response) were extracted, and at each time point picture luminance was regressed out. They were then averaged across the two time points and mean-subtracted, and in the end 112 extracted volumes (neural responses to 112 pictures) were obtained. The number of volumes was determined based on its performance in classifying picture categories (S.A. 2).

For the brand imagery data, we selected three consecutive volumes (at 0s, 2.3s, and 4.6s, spanning in total 6.9s) closest to the brand logos' onset time (again adding 6s to account for hemodynamic delay). We chose the brand logo onset instead of the visualization phase onset (4s after brand logo onset) because participants reported they began visualizing as soon as they saw the brand logo, even though we cued the participants to do so at the visualization phase. (Varying the number of volumes did not materially affect the results; see S.A. 4.). Separately at each time point, brand logo luminance was regressed out. They were then averaged across the three time points and mean-subtracted. In the end, 84 extracted volumes (neural responses to 14 brands × 6 repetitions) were obtained.

Content decoding. Within participants, we trained four support vector machine (SVM) classifiers on the picture viewing data, one for each social context (professional, intimate, familial, communal). We then passed the brand imagery data to the classifiers, and obtained four decision values (i.e., signed distances from the classification hyperplanes) for each of the 84 extracted volumes (14 brands × 6 repetitions), which were then averaged by brand. Each of the 14 brands therefore had four context scores ('neural context score'), each indicating the degree of pattern similarity of the brand to each of the four social context templates based on the participant's neural responses.

Profile compiling. Separately, within participant, we calculated the correlation distances between the 84 extracted volumes (14 brands × 6 repetitions) in the brand imagery task and the 112 extracted volumes in the picture viewing task, resulting in an 84 × 112 matrix, which was then averaged by brand. Each of the 14 brands therefore had a 112-feature vector ('neural profile'), with each feature being the correlation distance to each picture. In effect, a brand's neural profile is a representation of an individual's perception of that brand's image, expressed in the degrees of resemblance to the 112 template pictures. We used the neural profiles of brand image to compute two matrices: An interbrand disparity matrix within each participant, which describes how neural profiles among brands are similar or different within a given participant; and an intersubject disparity matrix within each brand, which describes how neural profiles among participants are similar or different within a given brand.

Identifying Brain Areas Associated with Social Context Processing

A total number of 3,173 voxels (85.7cm^3) were identified in the voxel selection process. (Brain areas with significantly different activation levels in pairwise social context contrasts are listed in Table S1 in the web appendix.) The resultant ROI mask covers several areas associated with visual processing, episodic memory, self-awareness and the default network, including occipital cortex, precuneus, posterior cingulate cortex, parahippocampal gyrus, and temporoparietal junction (Figure 4).

To verify whether the selected voxels could indeed be used to reliably differentiate various social contexts, we performed a cross-validated classification test by linear SVM within each participant using the picture viewing data, with the four blocks as holdout folds. The average classification accuracy is 44.9%, SD = 8.2%, which is significantly above chance at 25% ($t(36) = 14.6$, $p < .0001$), indicating that the voxels contained information for social context decoding. This performance was roughly in line with the multi-category classification accuracy of complex stimuli in existing neural decoding literature, such as classifying natural scene pictures (31% with chance level at 16%, Walther et al. 2009), or emotional valence of speech (30% with chance level at 20%, Ethofer et al. 2009). Having established that our classifiers are able to distinguish between the different social contexts, we then proceeded to test our hypotheses.

Neural Responses during Brand Imagery Correlate with Individual's Brand Perception

We passed the brand imagery data to these classifiers to obtain four decision values (i.e., signed distances from the classification hyperplanes) for each brand, representing the likelihood that the neural responses evoked by the brand imagery reflected the four different social contexts. Thus, each of the 14 brands received four context scores ('neural context score'), each indicating the degree of pattern similarity of the brand to each of the four social context templates based on the participant's neural responses (see Figure 5, right panel).

We could then test how accurately the classifiers determined the visualized brand images in terms of these social contexts. We did so by comparing the neural context scores to the participants' responses in the follow-up brand perception survey, in which they indicated how they thought about a brand's intended social context (for example how much they thought the word 'family' fit Disney, et cetera, see Figure 5, left panel). To test to what extent the neural context scores corresponded with the self-report brand perceptions (H_1), we modeled participants' self-report brand perception with neural context scores using linear mixed-effects models with participants entered as random intercept, both separately for each social context and together with all contexts (Table 1). Overall, neural context scores significantly correlated with survey responses ($F(1,1501.28) = 15.7$, $p < .0001$), meaning that when a participant's neural responses to a brand (e.g., Disney) during the imagery task resembled those during viewing of similarly-themed pictures (e.g., pictures depicting family gatherings), the participant also judged that brand to be more strongly associated with that particular context. In separate analyses, neural context scores significantly correlated with survey responses in three contexts (professional, intimate and familial; *p*s < .05), while the coefficient for communal was not significant ($p = .43$).

These findings confirm our first hypothesis and show that participants' perception of a brand's image can be captured by the decoded neural representation of social contexts for that brand.

Similarity of Neural Profiles Reflect Individual's Perceived Brand Similarity

We investigated further whether individual neural profiles reflect idiosyncrasies in brand image perception. Following the analysis paradigm outlined by Kriegeskorte, Mur and Bandettini (2008), we calculated for each participant a matrix of interbrand disparity between all pairs of the 14 brands, using the correlation distances of the 112-feature neural profiles. In addition, we obtained from participants their explicit judgment of brand image similarity from the multi-arrangement task, i.e., the subjective interbrand distances that formed a 14 × 14 dissimilarity matrix for each participant.

The question we would like to answer is whether neural profiles extracted from brain activities reflected the participant's own perceived brand similarity (H_2). Pearson correlations between each participant's neural and self-report matrices were plotted in Figure 6A. The average correlation (after Fisher's *r*-to-*z* transformation, Silver & Dunlap, 1987) was .107, and the Fisher-transformed correlations were significantly different from zero ($t(36) = 6.16$, $p < .0001$). That is, if a participant judged two brands to be highly different in terms of brand image in the multi-arrangement task, the neural activation patterns evoked by the two brands of that participant were also highly different. In contrast, when the participant judged two brands to be similar, the evoked neural responses during brand imagery also had similar patterns. This shows that neural profiles indeed captured the individual's perceived brand similarity, thus confirming our second hypothesis.

STUDY 2: MARKETING IMPLICATIONS OF NEURAL PROFILES

In Study 1, we were able to build neural profiles of brand images that reflected the individual's self-report perception of the brands. In addition to looking at the relationship between individual neural responses and self-report brand perception, we reasoned that the aggregate neural responses of a group of consumers should offer information on brand image at large. We therefore investigated two possible implications: co-branding suitability and brand image strength (see Figure 3B, lower panel for an overview). Using the neural data collected in Study 1, we attempted to quantify the perceptual fit of brands, as rated by a larger external sample. This is especially relevant in co-branding (Blackett and Russell 2000), in which one product is branded by two independent brands (e.g., Betty Crocker cake mix and Hershey's chocolate), or advertising alliances (Samu, Krishnan, and Smith 1999), in which two brands enter into a partnership of joint promotion (e.g., GoPro camera and Redbull energy drink). Previous studies have shown that in order for such a strategy to be successful, one of the determining factors is brand 'fit', or consumers' perception of whether the partner brands are compatible in terms of brand concept or image (Helmig, Huber, and Leeflang 2008; van der Lans, Van den Bergh, and Dieleman 2014; Simonin and Ruth 1998). Here we posit that brands with similar neural profiles will be judged by consumers as suitable co-branding partners. We therefore propose that:

H_3: Similarity in neural profiles of brand image is positively associated with perceived suitability of co-branding.

Since we do not assume that individuals perceive brands the same way, we can obtain a measure of variation in brand image perception across individuals. This allows us to study consistency in brand image among consumers, which we refer to as brand image strength.

Although this concept is little researched in the literature, it has practical relevance to marketing practitioners. Intuitively, after exposure to effective marketing, different consumers should be able to form a similar set of mental associations with the brand; conversely, an ineffective brand building exercise would leave consumers to draw their own idiosyncratic conclusions with regard to the brand's image. In other words, brand image strength should manifest itself not only in terms of *image vividness* within a consumer, but also in terms of *image consistency* across a group of consumers. A strong-image brand, in this sense, is one about which most consumers make a similar constellation of associations, whereas a weak-image brand is one that fails to instill similar images among consumers. Thus our last hypothesis is that brands evaluated as having a stronger image should elicit more similar neural profiles across individuals. Our fourth hypothesis is therefore:

> *H_4: Brands that elicit more similar neural profiles across individuals are perceived to have a stronger brand image.*

Method

In order to obtain external ratings, we recruited 157 students (73 men, age range = 17-23, mean = 18.9, SD = 1.2) via the recruitment system of the university. They received course credit for their completion of a 30-minute questionnaire, which consisted of two parts:

Co-branding suitability. Participants were shown a series of brand pairs drawn from the 14 brands. For each brand pair, they answered a self-constructed co-branding suitability measure, which consisted of three questions, each with an unmarked VAS slider (0-100): 'Are these two brands a compatible fit?' (labels at opposing ends: 'not fitting at all' and 'a perfect fit'), 'If the two brands decide to co-sponsor an event (e.g. music festival, exhibition, tennis tournament, etc.), how natural would that feel to you?' ('very unnatural' and 'very natural'), 'If the two brands decide to develop a co-branded 'crossover' product, do you think it will more likely be a failure or a success?' ('most likely failure' and 'most likely success'). The default slider position was mid-point and participants were required to move each slider at least once. The co-branding suitability score of a given pair of brands is the average score of the three questions (Cronbach's $\alpha = .952$). Out of the possible 91 brand-pair combinations, each participant responded to a randomly selected subset of 45 pairs.

Brand image strength. In addition, they also completed the consumer-based brand equity scale (Yoo and Donthu 2001) for each of the 14 brands. This 10-item scale has three components: brand loyalty (3 items), perceived quality (2 items), and brand awareness/associations (5 items). Of particular interest is the brand awareness/associations dimension, which consists of items related to brand image strength (example items are: 'I can recognize [brand] among other competing brands' and 'Some characteristics of [brand] come to my mind quickly'). The wording of one item ('I can quickly recall the symbol or logo of [brand]') was changed to 'I can quickly recall the advertisements or marketing materials' to better suit the purpose of this study. Participants responded to each item with an unmarked VAS slider (0-100), with 'strongly disagree' and 'strongly agree' at opposing ends. The default slider position was mid-point and participants were required to move each slider at least once.

Co-Branding Suitability is Associated with Interbrand Neural Profile Disparity

We examined if, on an aggregate level, the neural profiles we obtained from Study 1 contain information about the characteristics of the brand's image that is representative of that segment of the consumer population (H_3). Note that raters in Study 2 were consumers from the same cultural background, similar age and gender distribution as the Study 1 sample. They evaluated co-branding suitability among the same 14 brands; based on their responses, we generated a 14 × 14 co-branding suitability matrix, with each element being the average co-branding suitability score of a pair of brands (see Figure 3B).

Similarly, the interbrand neural profile disparity matrices of the participants in Study 1 were averaged. We found the relationship between the aggregated interbrand neural profile disparity matrix and the co-branding suitability matrix to be significantly negative (Figure 6B, $r = -.384$, $p < .0001$). This means that the more similar two brands' neural profiles are, the more suitable they are perceived by consumers as co-branding partners, confirming our third hypothesis.

Brand Image Strength Correlates with Neural Profile Consistency

Lastly, we investigated the possible link between brand image strength and neural profile consistency (H_4). Neural profile consistency was calculated in the following way: for each brand, there were 37 neural profiles, one from each participant. Between every unique pair of participants (out of 666 possible combinations), the disparity of their neural profiles of the same brand (in terms of correlation distance) was calculated. The average score of all intersubject neural profile disparities was taken as an inverse measure of neural profile consistency.

Brand image strength was rated by participants in Study 2 based on their responses to the consumer-based brand equity scale. Exploratory factor analysis of the scale items suggested a two-factor structure, in which the first factor was the combination of brand loyalty (3 items) and perceived quality (2 items) subscales (Cronbach's alpha = .864; this factor is named 'brand attitude'), while the original brand association subscale (5 items) – our measure of brand image strength – remained intact as the second factor (Cronbach's alpha = .834).

Brand attitude did not significantly correlate with average intersubject neural profile disparity ($r = -.329$, $p = .255$ based on 10,000 random permutations of brands in calculating the intersubject disparity matrix; correlations with the original subscales, brand loyalty and perceived quality, were also not significant; r = -.322 and -.301, p = .266 and .293 respectively based on permutations.). In other words, neural profile consistency is not correlated with brand loyalty or perceived quality. However, the correlation between average intersubject neural profile disparity and brand image strength was significant (Figure 7, r = -.627, p = .013 based on permutations), meaning that brands which evoke more similar neural profiles across individuals indeed had a stronger brand image, thus confirming our fourth hypothesis.

GENERAL DISCUSSION

An important component of consumer-based brand equity research is to understand the constellation of associations evoked by a brand in the consumer's mind (Aaker 1991; Keller 1993, 2003). Brand image, in this sense, is the meaningful organization of this associative memory network. While marketing researchers often emphasize the link between having a strong brand image and market success, and the advertiser's role in it (Aaker and Biel 2013; Dahlen, Lange, and Smith 2010; Faircloth, Capella, and Alford 2001), assessing brand-building efforts has been difficult in part because there is no obvious reliable way to map out these mental associations in the consumer's mind. As a result, researchers often resort to indirect methods such as self-report questionnaires or qualitative interviews.

In this paper, we examined brand image in the consumer's mind by extracting information directly from their brain during brand image visualization. Using a set of naturalistic pictures depicting various user and usage contexts as profiling space, we were able to build neural profiles of brand images that reflected the individual's self-report perception of the brands

(Study 1). Moreover, in aggregate, the neural profiles were associated with co-branding suitability and offered a measure of brand image strength (Study 2). We thus provide a proof of concept of the neural approach in measuring brand image.

The current study extends previous neuroimaging studies on brand perception, notably by Yoon and associates (2006), and more recently, Chen, Nelson and Hsu (2015). In these two studies, participants rated whether an adjective suitably described a brand (in the former), or passively viewed brand logos and freely thought about them (in the latter). The current study used a cognitively more demanding task of visualization, in which participants needed to construct a mental image based on their perception of the brand. We found that brain areas sensitive to social context perception and involved in visual and emotional processing, episodic memory, and mentalizing, contained brand-specific information. These areas have significant overlap with the regions uncovered by Chen, Nelson and Hsu (2015) in their passive brand perception task, including occipital and temporal regions, precuneus, hippocampus and prefrontal areas. It shows that the active brand image visualization task applied in the current study at least partly shared the neural process of passive brand evaluation. More importantly, the current study extracted neural information from similar brain areas with a novel template-based profiling approach that (a) provided greater flexibility in organizing and measuring mental associations of brand image, (b) allowed individual variation in brand image, and (c) offered a potential measure of brand image strength.

Mapping Brand Associations by Neural Patterns

We found that neural profiles, created by comparing how the brain responds to brands with how the brain responds to template pictures, describe an individual’s brand image perception. Individual neural profiles also produce brand distance matrices that correlate well with how these participants report perceived similarities among brands. Our study adds to increasing efforts to capture idiosyncratic mental representations in the brain. While previous studies investigated neural pattern similarity on the perception of objects (Charest et al. 2014), words (Bruffaerts et al. 2013) and body parts (Bracci, Caramazza, and Peelen 2015), the current study examined neural representational similarity in mental associations evoked by cultural artifacts (consumer brands), suggesting the potential of this methodology in understanding how complex human knowledge is represented in the brain. For marketing research, looking into neural variability in brand image opens new avenues to study the evolution of brand image. In addition to brand repositioning programs (Simms and Trott 2007; Yakimova and Beverland 2005), studies showed that brand image changes due to spillover effects during co-branding or brand alliance programs (Washburn, Till, and Priluck 2004). Our approach can be used to trace such dynamic updating of brand image, and to learn how consumers acquire new mental associations as a result of marketing actions (van Osselaer and Janiszewski 2001). This quantifiable measure can be used by marketers to evaluate the effectiveness of brand image messaging.

This study is, to the best of our knowledge, the first attempt to predict co-branding suitability based on neural responses. Past marketing literature on co-branding and brand alliance emphasizes the importance of perceptual fit (Gammoh, Voss, and Chakraborty 2006; Simonin and Ruth 1998; Thompson and Strutton 2013) in determining the success of such endeavors. In Smith and Park’s (1992) formulation, perceptual fit includes aspects such as ‘product usage situations’. While there have been attempts to gauge these intangible aspects of perceptual fit through psychometric methods (e.g., Smith and Andrews 1995), the use of neuroimaging methods promises a new way to capture and quantify perceptual fit between brands.

Neural Reliability as Potential Quality Indicator of Consumer Experience

Finally, we found that the consistency with which a brand's image is neurally encoded across different consumers correlated with perceived brand image strength. There has been growing interest in understanding the implications of intersubject consistency in neural responses (Hasson, Malach, and Heeger 2010). Neuroimaging studies have shown that neural activities are often synchronized across individuals who process narratively rich stimuli, such as spoken stories (Silbert et al. 2014), speeches (Schmälzle et al. 2015), movies (Hasson, Malach, and Heeger 2010), and video clips (Nummenmaa et al. 2012). Moreover, the extent to which intersubject consistency occurs – commonly referred to as neural reliability – seems to be a measure of consumer engagement, in terms of viewership and ticket sales (Barnett and Cerf 2017; Dmochowski et al. 2014).

The current study extends this line of research in two ways. First, it demonstrated a novel application of neural reliability where the consumer experience in question is static. Neural reliability is most often measured in terms of *temporal* synchronization of a single voxel (time-series correlation) during dynamic stimuli processing (e.g., watching a TV show). The current study shows that *spatial* consistency across multiple voxels (spatial distance) during static stimuli processing (e.g., visualizing brand image) can also be a quality indicator, in this case the image strength of a brand. Second, it further showed the feasibility of what we would term as 'meta-pattern' analysis. Instead of calculating pattern similarity by comparing raw neural signals across participants, we first calculated the feature vector of each stimulus based on the relationships between its raw neural signals and those from the template set, and then obtain a pattern similarity measure from those feature vectors. As such, measuring neural reliability using fMRI data no longer requires the assumption of strict one-to-one anatomical correspondence among individuals, i.e., given the same stimuli, each person employs exactly the same brain area in exactly the same way, despite evidence to the contrary (Barch et al. 2013). In fact, in an exploratory analysis we used untransformed images in each participant's native brain space and created individually-calibrated masks (i.e., selecting voxels based on the participant's own contrast maps instead of the group's), and found that the findings were largely replicated (S.A. 8). Currently, it is not known whether meta-pattern analysis is applicable in contexts other than visualization, and whether such an approach offers additional insight over using raw neural signals. For example, instead of comparing voxel-wise time-series among viewers of a TV show, is it possible to first create a profiling space using a large set of emotional stimuli, then calculate moment-by-moment emotional feature vectors, and finally measure neural reliability based on those vectors? And will this approach offer better predictive value by allowing individual differences in neural processing (Hamann and Canli 2004)? Further research is required to answer these questions.

Robustness Analysis and Study Limitations

We conducted a series of robustness analyses, which are detailed in the web appendix. We varied both the number of volumes and voxels extracted in the picture viewing task (S.A. 2 and 3) and in the brand imagery task (S.A. 4 and 5). We excluded voxels in visual cortex to see if brand-related information was confined to visual processing (S.A. 6). Instead of raw voxel data, we modelled brain responses in a general linear model first and used the estimated parameters (beta images) for analysis (S.A. 7). We used untransformed brain images with individually-calibrated masks (S.A. 8), and re-created neural profiles with a subset of pictures (S.A. 9). Results were largely replicated in these robustness analyses. We also showed that neural profiles could be used to identify specific brands (S.A. 10); and neural responses appeared to be time-locked with the task (S.A. 11).

A fair question regarding the validity of the findings is to what extent the neural information we obtained from the task uniquely indeed captured brand image (as opposed to capturing, e.g., product category or quality). We believe that the current study does provide strong supportive evidence on this aspect. First, participants voluntarily spent about 30 to 45 minutes, at their own pace and without explicit time instruction, to create a visual imagery for each of the brands (about 2-3 minutes per brand), indicating a high level of engagement on their part in the task. Second, the two separate self-report measures, one relating to categorical evaluation and the other relating to interbrand similarity, provide converging evidence that brand image was indeed being measured. However, we acknowledge that the study was limited by the small number of brands. In order to better address this question, future research should include a larger number of brands while controlling for variation such as product category (e.g., using only car brands with diverse brand images).

It is not entirely clear whether the pre-scanner task was critical in evoking the neural responses to brands; that is, whether we would obtain similar results had the participants just seen the brand logos without the preparation task and without explicit instructions on visualization during scanning. We note that participants reported they started visualizing at the onset of brand logo presentation, and that neural profiles appeared to be time-locked to the brand logo presentation (instead of the imagery phase 4s later; S.A. 11). Whether this is due to the extended practice during the preparation task or an indication of automatic processing remains to be answered. Further research is needed to determine the extent of automaticity of brand image processing.

We did not find a significant relationship between the neural score of the communal context ('party') and the corresponding self-report rating. There could be several reasons for this. First, in the questionnaire, participants were asked to rate how well the word 'party' described the brands. It might well be that the term was overly vague and participants inferred a different meaning. (It should be noted that the self-report rating took place one week after the scanning, and therefore any direct recall of the pictures at that time should be minimal.) Second, pictures for the communal context mostly depicted people in a typical party scene with music and drinks. They might not sufficiently capture the variation in the actual mental images created by the participants. The potential lack of correspondence between the text label, the visual stimuli, and the mental images underlines another limitation of this study, which is that the quality of the profiling space was dependent on the choice of templates. Although our concern was mitigated by the fact that neural profiles were robust to using only subsets of the pictures without the communal context (S.A. 10), further replication efforts are needed to find out what visual stimuli should be included to represent the communal context.

Finally, we tested whether self-report data in Study 1 also predicted brand image strength and co-branding suitability in Study 2. For brand image strength, the intersubject reliability in self-report scores did not correlate with brand image strength (S.A. 12). Comparing the relative strength of neural and self-report data in predicting co-branding suitability (S.A. 13), we found that both neural and self-report data predicted co-branding suitability, and that neural data did not explain additional variance beyond self-report data. This makes sense, since reporting on brand image similarity and co-branding suitability is essentially answering a highly similar question. A more interesting question would be to what extent neural data could predict actual co-branding success in the market. However, at present we do not have such real market data.

Further research is required to determine the relative merits of self-report and neural data in predicting the success of such partnerships using real-world market outcomes (Venkatraman et al. 2015).

Template-Based Neural Profiling: Possible Directions for Future Application and Research

We believe that a big advantage of template-based neural profiling is that it offers a large flexibility in choosing the relevant profiling space such that it is best suited to a particular marketing question. Marketers can choose to focus on and study very specific associations which they believe to be crucial in the market they operate in. As a result, future studies can extend this approach in several directions. First, other types of visual templates can be explored. For example, whereas we used pictures of different social contexts in order to decode user and usage imagery, pictures evoking various emotions can be used instead to produce an affect-based neural profile of brand image. One such candidate is the International Affective Picture System (Lang, Bradley, and Cuthbert 2008), which has the advantage of having well validated valence and arousal scoring for each picture in the collection.

Second, whereas we chose pictures of pre-defined categories for profiling, it is possible to create a model-free profiling space instead by sampling naturally-occurring stimuli without category-based selection. In one such example (Norman-Haignere, Kanwisher, and Mcdermott 2015), participants listened to 165 commonly-heard natural sounds (e.g., door knocking, coughing, etc) during fMRI scanning, and based on their neural activations six sound-response components were found in the auditory cortex. A model-free profiling space might have the advantage of better capturing latent dimensions of neural response patterns, and therefore producing neural profiles that better describe brand image.

Finally, this study has demonstrated the possibility of extracting knowledge from consumers without resorting to verbalization, potentially leading to new areas of academic and applied research on consumer experience. Neuroscientific research has helped reveal neural representations of sensory experience, not only sounds but also tastes (Smits et al. 2007), touch (Gallace and Spence 2009), smells (Lombion et al. 2009), as well as multi-modal sensations (Barros-Loscertales et al. 2012; Castriota-Scanderbeg et al. 2005). With new methodological advances in neuroimaging research such as pattern analysis and machine learning, future research should capitalize on this rapid development in order to capture in richer detail consumer experience with products and brands, which is by nature multi-sensory and often defies verbal description (Smidts et al. 2014). By demonstrating a novel approach to capture consumers' visual representations of brand image, this study represents a first step towards understanding sensorial consumer knowledge and experience.

Figure 1. Overview of brand-based decoding and template-based profiling approaches

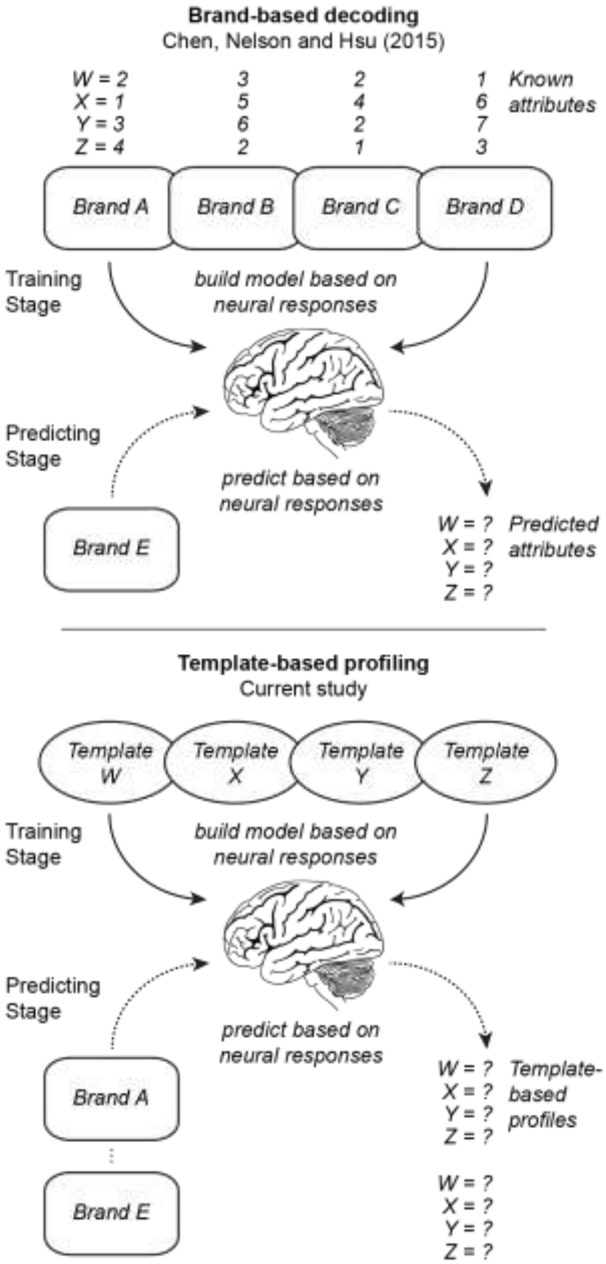


Figure 2. (A) Procedure of scanning task and (B) example screenshot of multiple arrangement task

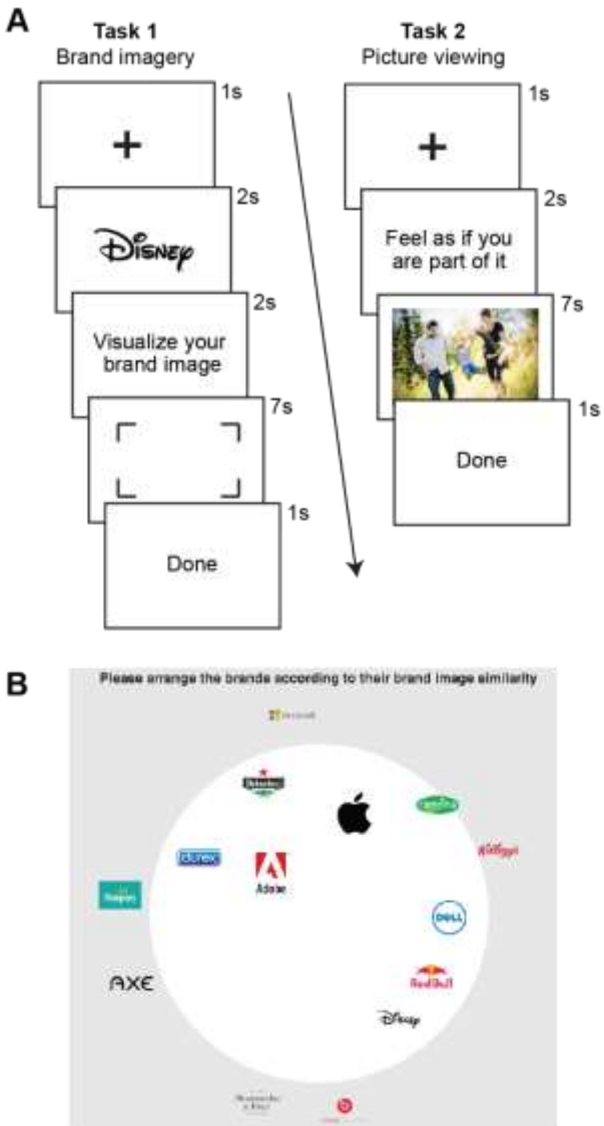


Figure 3. Schematic diagram of (A) the analysis and (B) the hypotheses

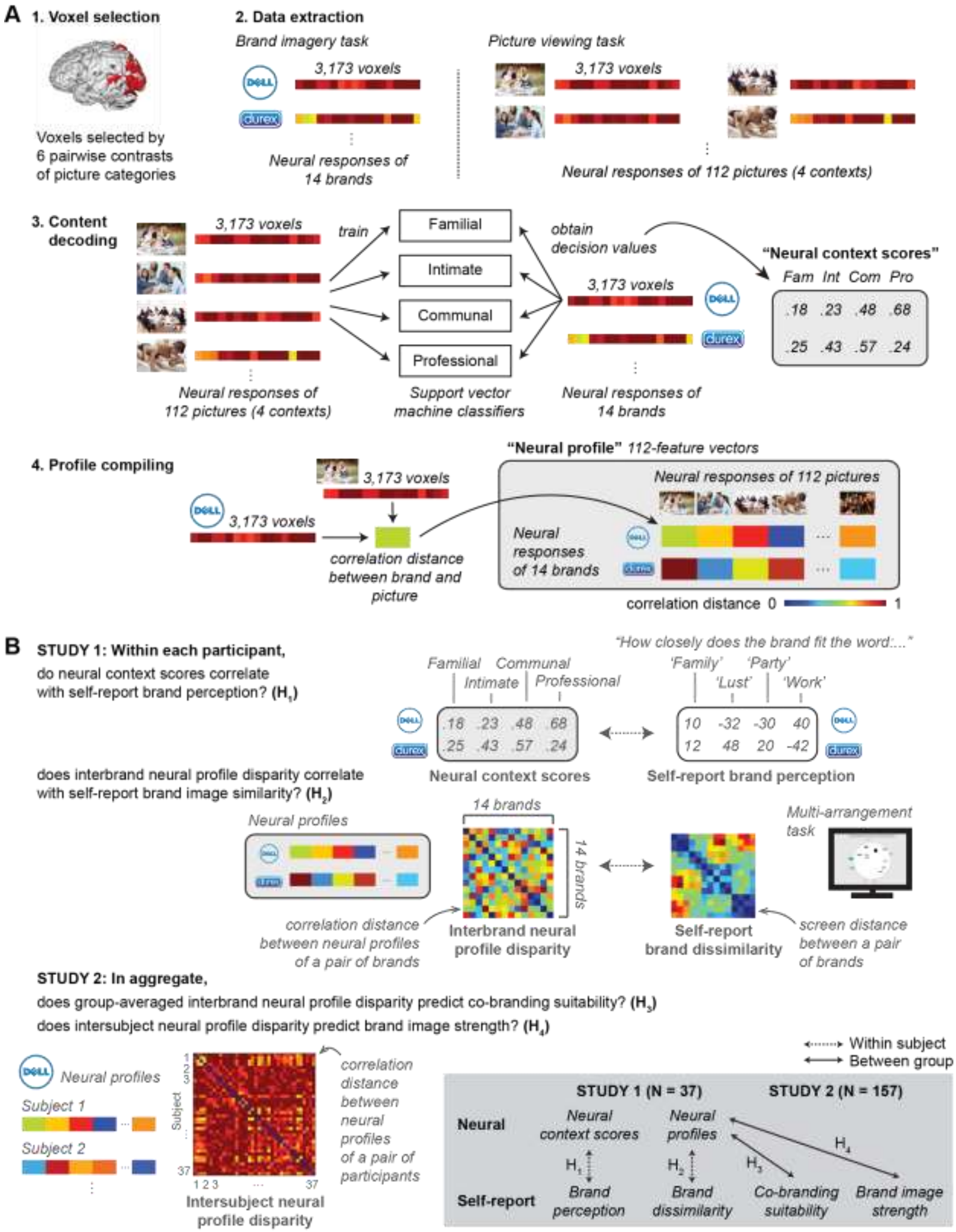


Figure 4. Voxels selected from six contrasts using 1% threshold in each direction, covering several areas associated with episodic memory, self-awareness and the default network, including precuneus, posterior cingulate cortex, parahippocampal gyrus, and temporoparietal junction, in addition to lateral and ventromedial prefrontal cortices.

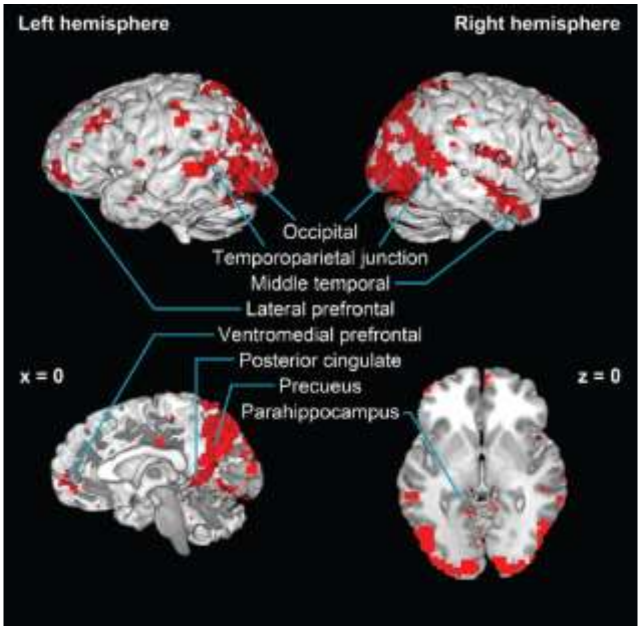
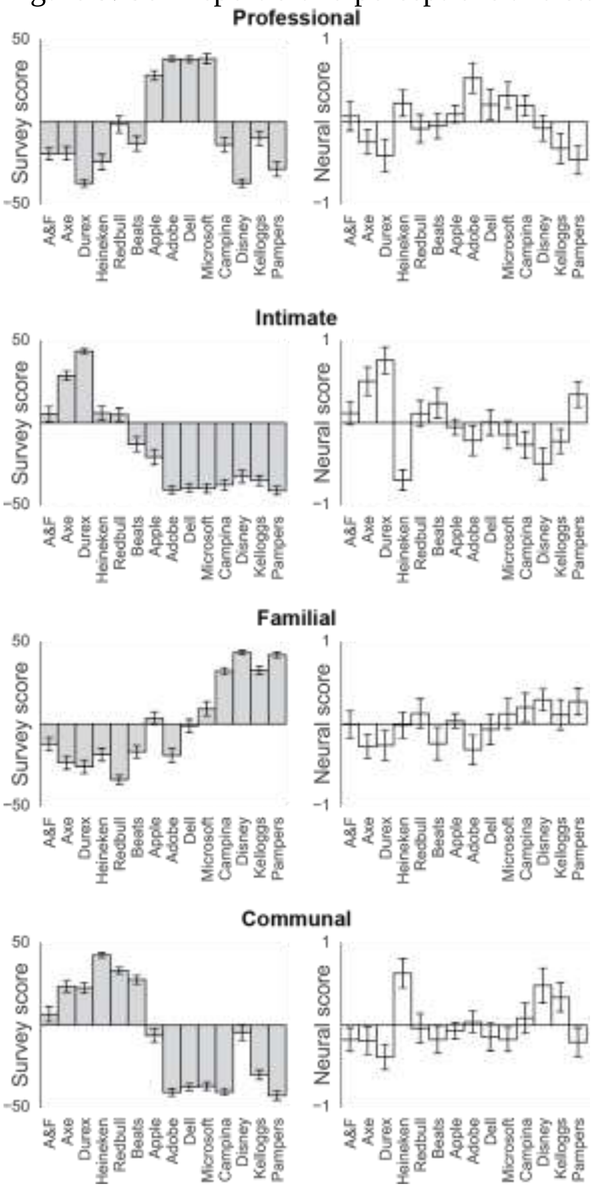


Figure 5. Self-report brand perceptions and standardized neural context scores



A&F = Abercrombie & Fitch; Neural scores were z-scored individually and within category.

Table 1. Linear mixed-effects models (participants as random intercepts) of self-report brand perceptions with standardized neural context scores

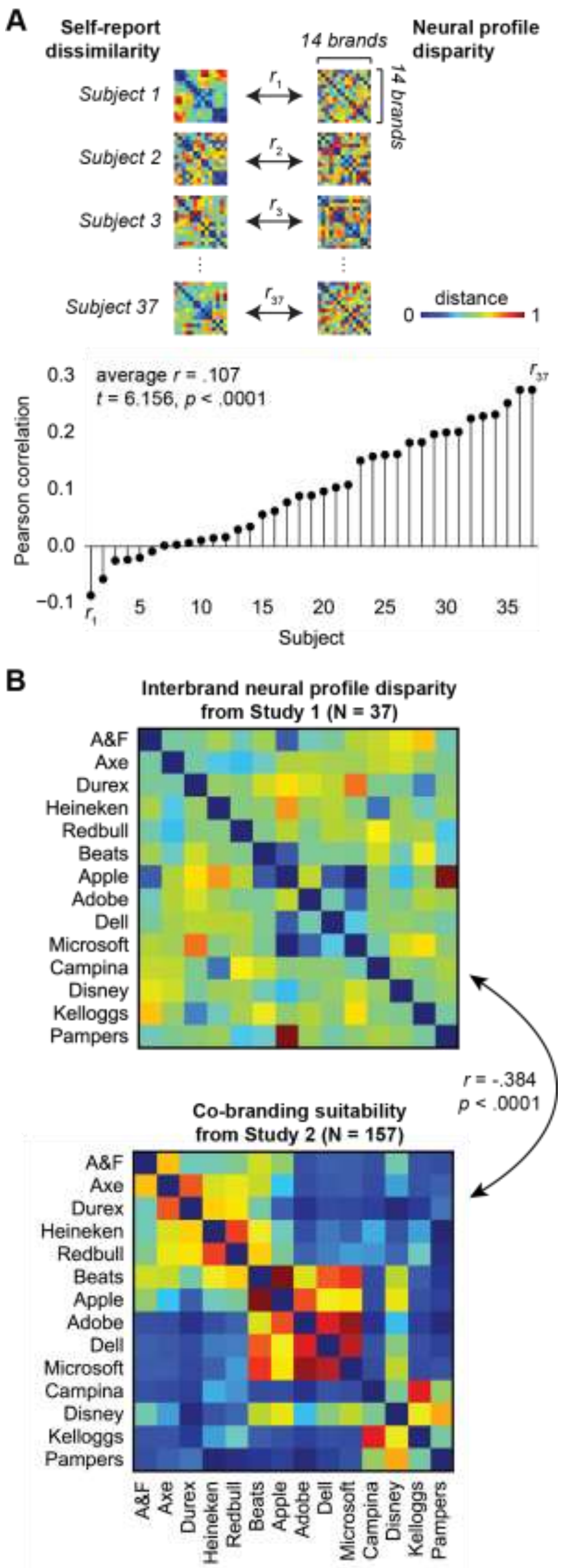
Model	1	2	3	4	5
Self-report brand perception	Professional	Intimate	Familial	Communal	Together
Neural context score					
F statistics of fixed effects					
Neural score	6.1*	16.9***	4.4*	0.6	15.7***
Context					22.1***
Neural score × Context					0.7
Marginal R^2	.016	.042	.012	.002	.046
Coefficient for each context					
Professional	.185				.194
Intimate		.141			.104
Familial			.206		.196
Communal				.061	.062

* $p < .05$; ** $p < .01$; *** $p < .001$

Note 1: In models 1-4, context scores were modelled separately; they were modelled together in model 5.

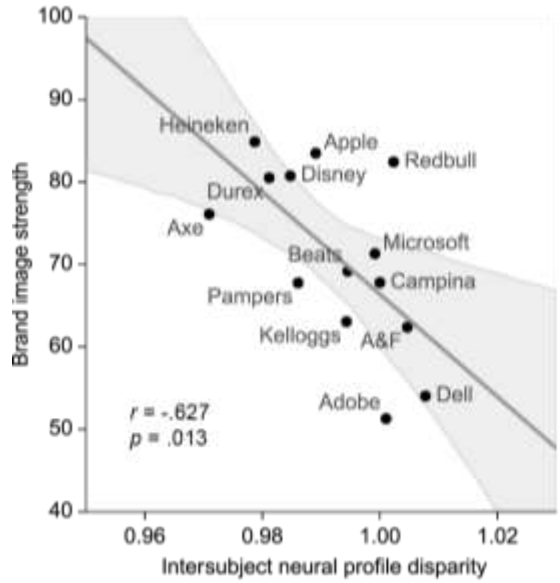
Note 2: Marginal R^2 is a measure of variance explained by fixed factors.

Figure 6. (A) Individual correlations between self-report brand image dissimilarity and interbrand neural profile disparity. Correlations are sorted in ascending order in the plot. (B) Co-branding suitability from Study 2 participants and aggregated interbrand neural profile disparity from Study 1 participants.



A&F = Abercrombie & Fitch

Figure 7. Intersubject neural brand profile disparity, brand image strength and brand attitude. P-value was calculated by Monte Carlo sampling of neural profiles (10,000 permutations).



A&F = Abercrombie & Fitch

REFERENCES

Aaker, David A. (1991), *Managing brand equity : capitalizing on the value of a brand name,* New York: Free Press.

——— and Alexander L. Biel (2013), *Brand Equity and Advertising : Advertising's Role in Building Strong Brands.*, Taylor and Francis.

Aaker, Jennifer (1997), "Dimensions of brand personality," *Journal of Marketing Research*, 34 (3), 347–56.

Alba, Joseph W and J Wesley Hutchinson (1987), "Dimensions of Consumer Expertise," *Source Journal of Consumer Research*, 13 (4), 411–54.

Babin, Laurie A. and Alvin C. Burns (1997), "Effects of Print Ad Pictures and Copy Containing Instructions to Imagine on Mental Imagery That Mediates Attitudes," *Journal of Advertising*, 26 (3), 33–44.

Barch, Deanna M., Gregory C. Burgess, Michael P. Harms, Steven E. Petersen, Bradley L. Schlaggar, Maurizio Corbetta, Matthew F. Glasser, Sandra Curtiss, Sachin Dixit, Cindy Feldt, Dan Nolan, Edward Bryant, Tucker Hartley, Owen Footer, James M. Bjork, Russ Poldrack, Steve Smith, Heidi Johansen-Berg, Abraham Z. Snyder, and David C. Van Essen (2013), "Function in the human connectome: Task-fMRI and individual differences in behavior," *NeuroImage*, 80, 169–89.

Barnett, Samuel B. and Moran Cerf (2017), "A ticket for your thoughts: Method for predicting content recall and sales using neural similarity of moviegoers," *Journal of Consumer Research*, 44 (1), 160–81.

Barros-Loscertales, Alfonso, Julio González, Friedemann Pulvermüller, Noelia Ventura-Campos, Juan Carlos Bustamante, Víctor Costumero, María Antonia Parcet, and César Ávila (2012), "Reading salt activates gustatory brain regions: FMRI evidence for semantic grounding in a novel sensory modality," *Cerebral Cortex*, 22 (11), 2554–63.

Blackett, Tom and Nick Russell (2000), "Co-branding — the science of alliance," *Journal of Brand Management*, 7 (3), 161–70.

Blumstein, Philip and Peter Kollock (1988), "Personal relationships," *Annual Review of Sociology*, 14 (1), 467–90.

Bracci, Stefania, Alfonso Caramazza, and Marius V. Peelen (2015), "Representational Similarity of Body Parts in Human Occipitotemporal Cortex," *Journal of Neuroscience,* 35 (38), 12977–85.

Brakus, J. Joško, Bernd H Schmitt, and Lia Zarantonello (2009), "Brand Experience: What Is It? How Is It Measured? Does It Affect Loyalty?," *Journal of Marketing*, 73 (3), 52–68.

Bruffaerts, Rose, Patrick Dupont, Ronald Peeters, Simon De Deyne, Gerrit Storms, and Rik Vandenberghe (2013), "Similarity of fMRI Activity Patterns in Left Perirhinal Cortex Reflects Semantic Similarity between Words," *Journal of Neuroscience*, 33 (47), 18597–607.

Castriota-Scanderbeg, Alessandro, Gisela E. Hagberg, Antonio Cerasa, Giorgia Committeri, Gaspare Galati, Fabiana Patria, Sabrina Pitzalis, Carlo Caltagirone, and Richard Frackowiak

(2005), “The appreciation of wine by sommeliers: A functional magnetic resonance study of sensory integration,” *NeuroImage*, 25 (2), 570–78.

Charest, Ian, Rogier A. Kievit, Taylor W Schmitz, Diana Deca, and Nikolaus Kriegeskorte (2014), “Unique semantic space in the brain of each beholder predicts perceived similarity.,” *Proceedings of the National Academy of Sciences of the United States of America*, 111 (40), 14565–70.

Chen, W, T Kato, X H Zhu, S Ogawa, D W Tank, and K Ugurbil (1998), “Human primary visual cortex and lateral geniculate nucleus activation during visual imagery.,” *Neuroreport*, 9 (16), 3669–74.

Chen, Yu-Ping, Leif D. Nelson, and Ming Hsu (2015), “From ‘Where’ to ‘What’: Distributed Representations of Brand Associations in the Human Brain,” *Journal of Marketing Research*, 52 (4), 453–66.

Cichy, Radoslaw M, Jakob Heinzle, and John-Dylan Haynes (2012), “Imagery and perception share cortical representations of content and location.,” *Cerebral cortex (New York, N.Y. : 1991)*, 22 (2), 372–80.

Coulter, Robin Higie and Gerald Zaltman (1994), “Using The Zaltman Metaphor Elicitation Technique to Understand Brand Images,” *Advances in Consumer Research*.

Cutler, Bob D, S Altan Erdem, and Rajshekhar G Javalgi (1997), “Advertiser’s relative reliance on collectivism-individualism appeals: a cross-cultural study,” *Journal of International Consumer Marketing*, 9 (3), 43–55.

Dahlen, Micael., Fredrik. Lange, and Terry Smith (2010), *Marketing communications : a brand narrative approach*, Wiley.

Dmochowski, Jacek P., Matthew A. Bezdek, Brian P. Abelson, John S. Johnson, Eric H. Schumacher, and Lucas C. Parra (2014), “Audience preferences are predicted by temporal reliability of neural processing,” *Nature Communications*, 5.

Esch, Franz-Rudolf, Thorsten Möll, Bernd Schmitt, Christian E Elger, Carolin Neuhaus, and Bernd Weber (2012), “Brands on the brain: Do consumers use declarative information or experienced emotions to evaluate brands?,” *Journal of Consumer Psychology*, 22, 75–85.

Ethofer, Thomas, Dimitri Van De Ville, Klaus Scherer, and Patrik Vuilleumier (2009), “Decoding of Emotional Information in Voice-Sensitive Cortices,” *Current Biology*, 19 (12), 1028–33.

Faircloth, James B., Louis M. Capella, and Bruce L. Alford (2001), “The Effect of Brand Attitude and Brand Image on Brand Equity,” *Journal of Marketing Theory & Practice*, 9 (3), 61–75.

Fournier, Susan (1998), “Consumers and Their Brands: Developing Relationship Theory in Consumer Research,” *Journal of Consumer Research*, 24 (4).

Gallace, Alberto and Charles Spence (2009), “The cognitive and neural correlates of tactile memory.,” *Psychological bulletin*, 135 (3), 380–406.

Gammoh, Bashar S., Kevin E. Voss, and Goutam Chakraborty (2006), “Consumer evaluation of brand alliance signals,” *Psychology and Marketing*, 23 (6), 465–86.

Hamann, Stephan and Turhan Canli (2004), "Individual differences in emotion processing," *Current Opinion in Neurobiology*.

Hasson, Uri, Rafael Malach, and David J Heeger (2010), "Reliability of cortical activity during natural stimulation," *Trends in cognitive sciences*, 14 (1), 40–48.

Helmig, Bernd, Jan-Alexander Huber, and Peter S. H. Leeflang (2008), "Co-branding: The State of the Art," *Schmalenbach Business Review*, 60 (4), 359–77.

Henderson, Pamela W, Joseph A Cote, Siew Meng Leong, and Bernd Schmitt (2003), "Building strong brands in Asia: selecting the visual components of image to maximize brand strength," *International Journal of Research in Marketing*, 20 (4), 297–313.

Herzog, Herta (1963), "Behavioral science concepts for analyzing the consumer," *Marketing and the behavioral sciences*, 76–86.

Horikawa, T., M. Tamaki, Y. Miyawaki, and Y. Kamitani (2013), "Neural Decoding of Visual Imagery During Sleep," *Science*, 340 (6132).

John, Deborah Roedder, Barbara Loken, Kyeongheui Kim, and Alokparna Basu Monga (2006), "Brand Concept Maps: A Methodology for Identifying Brand Association Networks," *Journal of Marketing Research*, 43 (4), 549–63.

Keller, Kevin Lane (1993), "Conceptualizing, Measuring, and Managing Customer-Based Brand Equity," *Journal of Marketing*, 57 (1), 1.

——— (2001), "Building Customer-Based Brand Equity : A Blueprint for Creating Strong Brands Building Customer-Based Brand Equity : A Blueprint for Creating Strong Brands," *Journal of Marketing Communications*, 15 (2–3), 139–55.

——— (2003), "Brand Synthesis: The Multidimensionality of Brand Knowledge," *Journal of Consumer Research*, 29 (4), 595–600.

Kirmani, Amna and Valarie Zeithaml (1993), "Advertising, perceived quality, and brand image," in *Brand Equity & Advertising: Advertising's Role in Building Strong Brands*, D. A. Aaker and A. Biel, eds., Hillsdale, NJ: Lawrence Erlbaum Associates, 143–62.

Klucharev, Vasily, Ale Smidts, and Guillén Fernández (2008), "Brain mechanisms of persuasion: How 'expert power' modulates memory and attitudes," 3 (4), 353–66.

Kosslyn, Stephen M., Giorgio Ganis, and William L. Thompson (2001), "Neural foundations of imagery," *Nature Reviews Neuroscience*, 2 (9), 635–42.

——— and William L. Thompson (2003), "When is early visual cortex activated during visual mental imagery?," *Psychological Bulletin*, 129 (5), 723–46.

Kriegeskorte, Nikolaus and Marieke Mur (2012), "Inverse MDS: Inferring dissimilarity structure from multiple item arrangements," *Frontiers in Psychology*, 3 (JUL).

———, ———, and Peter a. Bandettini (2008), "Representational similarity analysis - connecting the branches of systems neuroscience.," *Frontiers in systems neuroscience*, 2 (November), 4.

Krishna, Aradhna (2012), "An integrative review of sensory marketing: Engaging the senses to affect perception, judgment and behavior," *Journal of Consumer Psychology*, 22 (3), 332–51.

——— and Norbert Schwarz (2014), “Sensory marketing, embodiment, and grounded cognition: A review and introduction,” *Journal of Consumer Psychology*, 24 (2), 159–68.

Krishnan, H.S. (1996), “Characteristics of memory associations: A consumer-based brand equity perspective,” *International Journal of Research in Marketing*, 13 (4), 389–405.

LaBarbera, P.A., P. Weingard, and E.A. Yorkston (1998), “Matching the message to the mind: Advertising imagery and consumer processing styles,” 38 (5), 29–42.

Lang, Peter J, Margaret M Bradley, and Bruce N Cuthbert (2008), “International affective picture system (IAPS): Affective ratings of pictures and instruction manual,” *Technical report A-8*, Gainesville, FL: Center for Research in Psychophysiology, University of Florida.

van der Lans, Ralf, Bram Van den Bergh, and Evelien Dieleman (2014), “Partner Selection in Brand Alliances: An Empirical Investigation of the Drivers of Brand Fit,” *Marketing Science*, 33 (4), 551–66.

Lombion, Sandrine, Alexandre Comte, Laurent Tatu, Gérard Brand, Thierry Moulin, and Jean Louis Millot (2009), “Patterns of cerebral activation during olfactory and trigeminal stimulations,” *Human Brain Mapping*, 30 (3), 821–28.

Low, George S. and Charles W. Lamb (2000), “The measurement and dimensionality of brand associations,” *Journal of Product & Brand Management*, 9 (6), 350–70.

McClure, Samuel M, Jian Li, Damon Tomlin, Kim S Cypert, Latané M Montague, and P Read Montague (2004), “Neural Correlates of Behavioral Preference for Culturally Familiar Drinks,” *Neuron*, 44, 379–87.

Mur, Marieke, Mirjam Meys, Jerzy Bodurka, Rainer Goebel, Peter A. Bandettini, and Nikolaus Kriegeskorte (2013), “Human object-similarity judgments reflect and transcend the primate-IT object representation,” *Frontiers in Psychology*, 4 (MAR).

Norman-Haignere, Sam, Nancy G Kanwisher, and Josh H Mcdermott (2015), “Distinct Cortical Pathways for Music and Speech Revealed by Hypothesis-Free Voxel Decomposition,” *Neuron*, 88 (6), 1281–96.

Nummenmaa, Lauri, Enrico Glerean, Mikko Viinikainen, I. P. Jaaskelainen, Riitta Hari, Mikko Sams, Iiro P Jääskeläinen, Riitta Hari, and Mikko Sams (2012), “Emotions promote social interaction by synchronizing brain activity across individuals,” *Proceedings of the National Academy of Sciences*, 109 (24), 9599–9604.

O’Craven, K. M. and N. Kanwisher (2000), “Mental Imagery of Faces and Places Activates Corresponding Stimulus-Specific Brain Regions,” *Journal of Cognitive Neuroscience*, 12 (6), 1013–23.

van Osselaer, Stijn M. J. and Chris Janiszewski (2001), “Two Ways of Learning Brand Associations,” *Journal of Consumer Research*, 28 (2), 202–23.

Park, C. Whan, Bernard J. Jaworski, and Deborah J. Maclnnis (1986), “Strategic Brand Concept-Image Management,” *Journal of Marketing*, 50 (4), 135.

Plassmann, Hilke, John O’Doherty, Baba Shiv, and Antonio Rangel (2008), “Marketing actions can modulate neural representations of experienced pleasantness,” 105 (3), 1050–54.

———, Thomas Zoëga Ramsøy, and Milica Milosavljevic (2012), “Branding the brain: A critical review and outlook,” *Journal of Consumer Psychology*, 22 (1), 18–36.

———, Vinod Venkatraman, Scott A. Huettel, and Carolyn Yoon (2015), “Consumer Neuroscience: Applications, Challenges, and Possible Solutions,” *Journal of Marketing Research*, 52 (4), 427–35.

Reynolds, Thomas J and Jonathan Gutman (1988), “Laddering theory, method, analysis, and interpretation,” *Journal of Advertising Research*, 28 (1), 11–31.

Roland, P.E. and B. Gulyás (1994), “Visual imagery and visual representation,” *Trends in Neurosciences*.

Roth, Martin S (1994), “Innovations in Defining and Measuring Brand Image,” *Advances in Consumer Research*, 21 (1), 495.

Samu, Sridhar, H Shanker Krishnan, and Robert E Smith (1999), “Using advertising alliances for new product introduction: Interactions between product complementarity and promotional strategies,” *Journal of Marketing*, 63 (1), 57–74.

Schaefer, Michael and Michael Rotte (2007), “Favorite brands as cultural objects modulate reward circuit,” 18 (2), 141–45.

Schmälzle, Ralf, Frank E. K. Häcker, Christopher J. Honey, and Uri Hasson (2015), “Engaged listeners: shared neural processing of powerful political speeches,” *Social Cognitive and Affective Neuroscience*, 10 (8), 1137–43.

Silbert, Lauren J, Christopher J. Honey, Erez Simony, David Poeppel, and Uri Hasson (2014), “Coupled neural systems underlie the production and comprehension of naturalistic narrative speech.,” *Proceedings of the National Academy of Sciences of the United States of America*, 111 (43), E4687-96.

Silver, N. Clayton and William P. Dunlap (1987), “Averaging correlation coefficients: Should Fisher’s z transformation be used?,” *Journal of Applied Psychology*, 72 (1), 146–48.

Simms, C. and P. Trott (2007), “An analysis of the repositioning of the ‘BMW Mini’ brand,” *Journal of Product & Brand Management*, 16 (5), 297–309.

Simonin, Bernard L. and Julie A. Ruth (1998), “Is a Company Known by the Company It Keeps? Assessing the Spillover Effects of Brand Alliances on Consumer Brand Attitudes,” *Journal of Marketing Research*, 35 (1), 30–42.

Slotnick, Scott D, William L Thompson, and Stephen M Kosslyn (2005), “Visual mental imagery induces retinotopically organized activation of early visual areas.,” *Cerebral cortex (New York, N.Y. : 1991)*, 15 (10), 1570–83.

Smidts, Ale, Ming Hsu, Alan G. Sanfey, Maarten A.S. Boksem, Richard B. Ebstein, Scott A. Huettel, Joe W. Kable, Uma R. Karmarkar, Shinobu Kitayama, Brian Knutson, Israel Liberzon, Terry Lohrenz, Mirre Stallen, and Carolyn Yoon (2014), “Advancing consumer neuroscience,” *Marketing Letters*, 25 (3), 257–67.

Smith, Daniel C. and Jonlee Andrews (1995), “Rethinking the effect of perceived fit on customers’ evaluations of new products,” *Journal of the Academy of Marketing Science*, 23 (1), 4–14.

——— and C Whan Park (1992), “The effetcs of brand extensions on market share and advertising efficiency,” *Journal of Marketing Research (JMR)*, 29 (3), 296–313.

Smits, Marion, Ronald R Peeters, Paul van Hecke, and Stefan Sunaert (2007), “A 3 T event-related functional magnetic resonance imaging (fMRI) study of primary and secondary gustatory cortex localization using natural tastants.,” *Neuroradiology*, 49 (1), 61–71.

Thompson, Kenneth and David Strutton (2013), “Revisiting perceptual fit in co- branding applications,” *Journal of Product & Brand Management*.

Venkatraman, Vinod, Angelika Dimoka, Paul A. Pavlou, Khoi Vo, William Hampton, Bryan Bollinger, Hal E. Hershfield, Masakazu Ishihara, and Russell S. Winer (2015), “Predicting Advertising Success Beyond Traditional Measures: New Insights from Neurophysiological Methods and Market Response Modeling,” *Journal of Marketing Research*, 52 (4), 436–52.

Walther, Dirk B., Eamon Caddigan, Fei-Fei Li, and Diane M. Beck (2009), “Natural Scene Categories Revealed in Distributed Patterns of Activity in the Human Brain,” *Journal of Neuroscience*, 29 (34).

Washburn, Judith H., Brian D. Till, and Randi Priluck (2004), “Brand alliance and customer-based brand-equity effects,” *Psychology and Marketing*, 21 (7), 487–508.

Yakimova, Raisa and Michael Beverland (2005), “The brand-supportive firm: An exploration of organisational drivers of brand updating,” *Journal of Brand Management*, 12 (6), 445–60.

Yoo, Boonghee and Naveen Donthu (2001), “Developing and validating a multidimensional consumer-based brand equity scale,” *Journal of Business Research*, 52 (1), 1–14.

Yoon, Carolyn, Angela H. Gutchess, Fred Feinberg, and Thad A. Polk (2006), “A Functional Magnetic Resonance Imaging Study of Neural Dissociations between Brand and Person Judgments,” *Journal of Consumer Research*, 33 (1), 31–40.

Zaltman, G and R. H. Coulter (1995), “Seeing the Voice of the Customer: Metaphor-Based Advertising Research,” *Journal of Advertising Research*, 35 (4), 35–51.

Web appendix

Brands Used in This Study

1. Abercrombie & Fitch
2. Axe
3. Durex
4. Heineken
5. Redbull
6. Beats
7. Apple
8. Adobe
9. Dell
10. Microsoft
11. Campina*
12. Disney
13. Kellogg's
14. Pampers

* Note: Campina is a dairy brand well-known in the country of research.

Instructions Used for Brand Imagery Formation

1. What is the brand image of Disney that **it portrays itself**? How do they want you to perceive the brand? Can you name a few adjectives that would describe the image **that the brand wants to convey**?

____

2. How would you understand the brand's motto / main message?

____

3. Do you think you have a clear or vague sense of this brand's image and/or message?

Very vague	1	2	3	4	5	6	7	Very clear

4. Now imagine that you are making a typical 'print advertisement' for this brand that would encapsulate the brand's image and/or message.

This 'print ad' will portray people using or interacting with this brand or its product.

Try to visualize, as vividly as possible, **the people, context, and mood** of that imaginary ad image. Make sure that this image evokes in you the same feelings that capture the 'essence' of that brand's image and/or message.

Can you describe what you visualize?

____

____

Examples of Descriptions of Brand Image Written by Participants

Kellogg's:

'A typical American family with white teeth and way too happy kids eat breakfast with cornflakes.'

Dell:

'A man is sitting behind his desk with a stack of paperwork. He has a Dell computer and begins step by step to work through the paperwork. It is done very quickly and the man feels satisfied with his computer.'

Abercrombie & Fitch:

'Two beautiful people, photo shopped and all, walk around looking sexy, of course wearing Abercrombie and Fitch. As they walk, people stare at them and their cloths.'

Durex:

'Two young adults (man and woman) having a sexually tensed situation with each other. The product sits in the right bottom corner.'

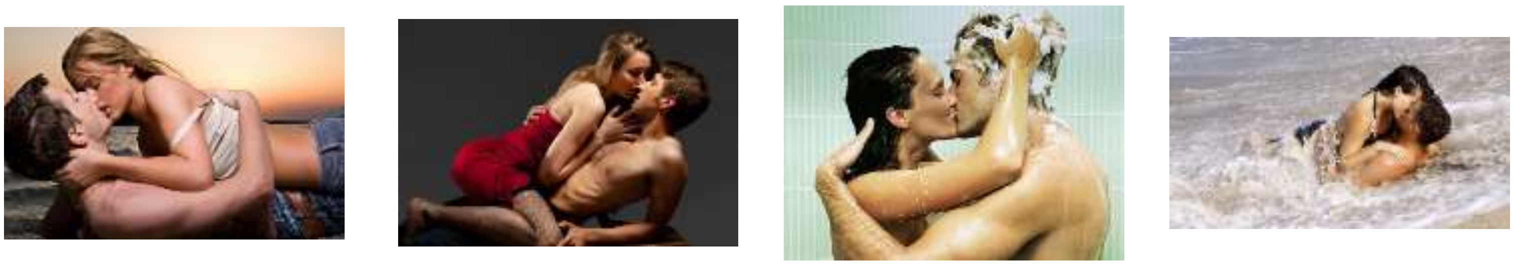
Beats:

'Young teens going to school with their headphones, cycling in the street, singing the song they hear. Happy.'

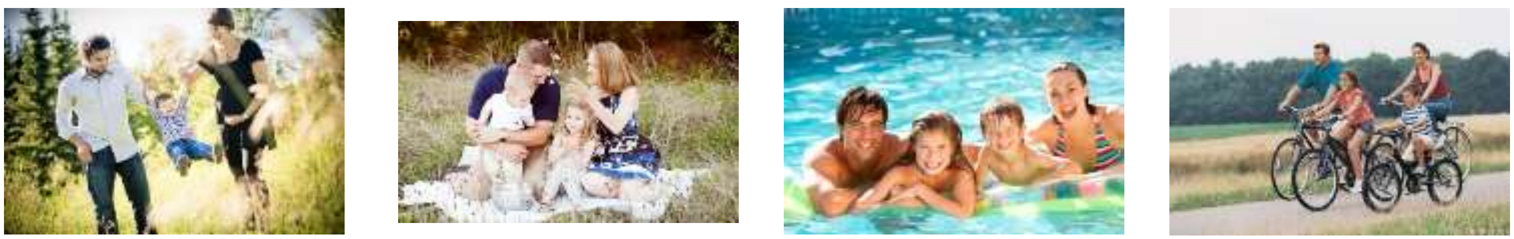
Examples of Visual Templates Used in the Picture Viewing Task

Professional

Intimate



Familial



Communal

Magnetic Resonance Data Acquisition Parameters

The functional magnetic resonance images were obtained using a 3T MRI system (General Electric). Functional scans were acquired by a T2*-weighted gradient-echo, echo-planar pulse sequence in ascending interleaved order (2.1 mm slice thickness, 1.0 mm slice gap, 2.5 × 2.5 mm in-plane resolution, 96 × 96 voxels per slice, flip angle = 77°, TE = 25ms, TR = 2300ms). A T1-weighted image was acquired for anatomical reference (1.0 × 1.0 × 1.0 mm resolution, 160 sagittal slices, TE = 2.35ms, TR = 7.21ms). The stimuli were projected onto a screen and participants viewed the screen through a mirror attached to the head coil.

Data Pre-Processing and Analysis

Data preprocessing was carried out using SPM12 (Statistical Parametric Mapping, Wellcome Department of Imaging Neuroscience, University College London, London, UK). Rigid-body transformations were applied to realign the volumes to the first volume. The anatomical image was co-registered with the mean functional image for each participant. Functional images were then normalised to Montreal Neurological Institute (MNI) space at voxel size 3 × 3 × 3mm. Finally, the normalised functional images were smoothed using a 4mm full-width-half-maximum Gaussian kernel.

Univariate analysis was carried out with the SPM12 software. For first-level fixed-effects analysis, we used general linear model with proportional scaling, AR(1) autocorrelation modeling, a 1/128-Hz high-pass filter, and regressor convolution with the SPM canonical hemodynamic response model. Covariates of no interest include average white matter and background signals. For group analysis, whole-brain images of contrasts were tested statistically using second level analyses, which treated participants as a random effect.

Multi-voxel pattern analysis was carried out in Python 2.7 with the PyMVPA toolbox (Hanke et al. 2009). Linear mixed-effects modeling (LMM) was computed in the statistical software R with the lme4 (Bates et al. 2015) and afex (Singmann et al. 2016) packages, while marginal R^2 was calculated by the MuMIN (Barton 2016) package.

Significant Brain Areas Found in Pairwise Comparisons of Social Contexts

Table S1. Top two clusters (in terms of peak *t* values) for each pairwise contrast of social contexts in both directions

Contrast	MNI coordinates			*k*	*t*	*p*	Anatomical area
	x	y	z				
Familial > Communal							
	-48	-55	20	1	5.78	.031	Temporal Mid L
	-3	-64	41	1	5.72	.037	Precuneus L
Familial < Communal							
	-15	-85	-7	25	7.38	< .001	Lingual L
	15	-85	-7	38	7.37	< .001	Lingual R
Familial > Intimate							
	0	-52	41	75	8.23	< .001	Precuneus L
	-18	-43	-13	16	7.16	< .001	Fusiform L
Familial < Intimate							
	-45	-76	-1	158	10.20	< .001	Occipital Mid L
	51	-61	-10	125	8.98	< .001	Temporal Inf R
Familial > Professional							
	-18	-97	2	3	6.03	.014	Occipital Mid L
	-18	-4	-16	3	5.97	.017	Amygdala L
Familial < Professional[*]							
	30	-43	-10	9	8.23	< .001	Fusiform R
Communal > Intimate							
	-9	-94	-4	106	11.55	< .001	Calcarine L
	15	-49	5	230	9.59	< .001	Lingual R
Communal < Intimate							
	-51	-73	-1	125	11.48	< .001	Occipital Mid L
	51	-61	-4	124	10.33	< .001	Temporal Inf R
Communal > Professional							
	18	-94	2	256	13.05	< .001	Calcarine R
	-21	-97	2	224	10.92	< .001	Occipital Mid L
Communal < Professional							
	51	2	-22	10	7.67	< .001	Temporal Mid R
	30	-43	-10	10	7.04	.001	Fusiform R
Intimate > Professional							
	51	-67	-4	262	10.29	< .001	Temporal Inf R
	-51	-73	-1	172	10.06	< .001	Occipital Mid L
Intimate < Professional							
	12	-49	2	279	9.69	< .001	Lingual R
	57	-10	-22	90	9.04	< .001	Temporal Mid R

Note: *k* denotes cluster size in voxels. L = left; R = right; Mid = middle; Inf = inferior; *p* values corrected for family-wise error.

[*] Only one significant cluster was identified.

Supplementary Analysis 1: Generalizability of Social Contexts

To confirm that the four social contexts (familial, communal, professional and intimate) were indeed represented in the user and usage imagery of a broader range of consumer brands, we conducted two Amazon Mechanical Turk studies. Specifically, we attempted to answer two questions: (a) Do consumers really think of brand image in terms of the four social contexts? (b) Can the four social contexts be used to differentiate consumer brands?

(A) Free generation

Sixty-six participants, in return for a payment of US$2.00, described the brand image of each of the 20 major American consumer brands (randomly drawn, for each participant, from a large set of 157 brands identified in www.brandirectory.com), using a similar prompt used in the main study ('Imagine you are making a typical advertisement for this brand that would encapsulate the brand's image. This ad will portray people using or interacting with this brand or its product.'). We then identified and extracted all nouns from the participants' responses, using the Natural Language Toolkit (available at www.nltk.org) and the WordNet database (Fellbaum 1998).

Of the unique 1,209 nouns obtained, a separate group of Mechanical Turk workers manually classified them into five categories: person, place, object, action, or none of the above. Since we were interested in understanding how participants visualized the social milieu for different brands, we chose to inspect the 277 place- and person-nouns generated by them. We found *prima facie* evidence that the four contexts could describe, to a significant but not comprehensive extent, the user and usage imagery of consumer brands.

Table S2. Place- and person-nouns extracted from the written descriptions of brand image of major American consumer brands among Amazon Mechanical Turk participants (N = 66)

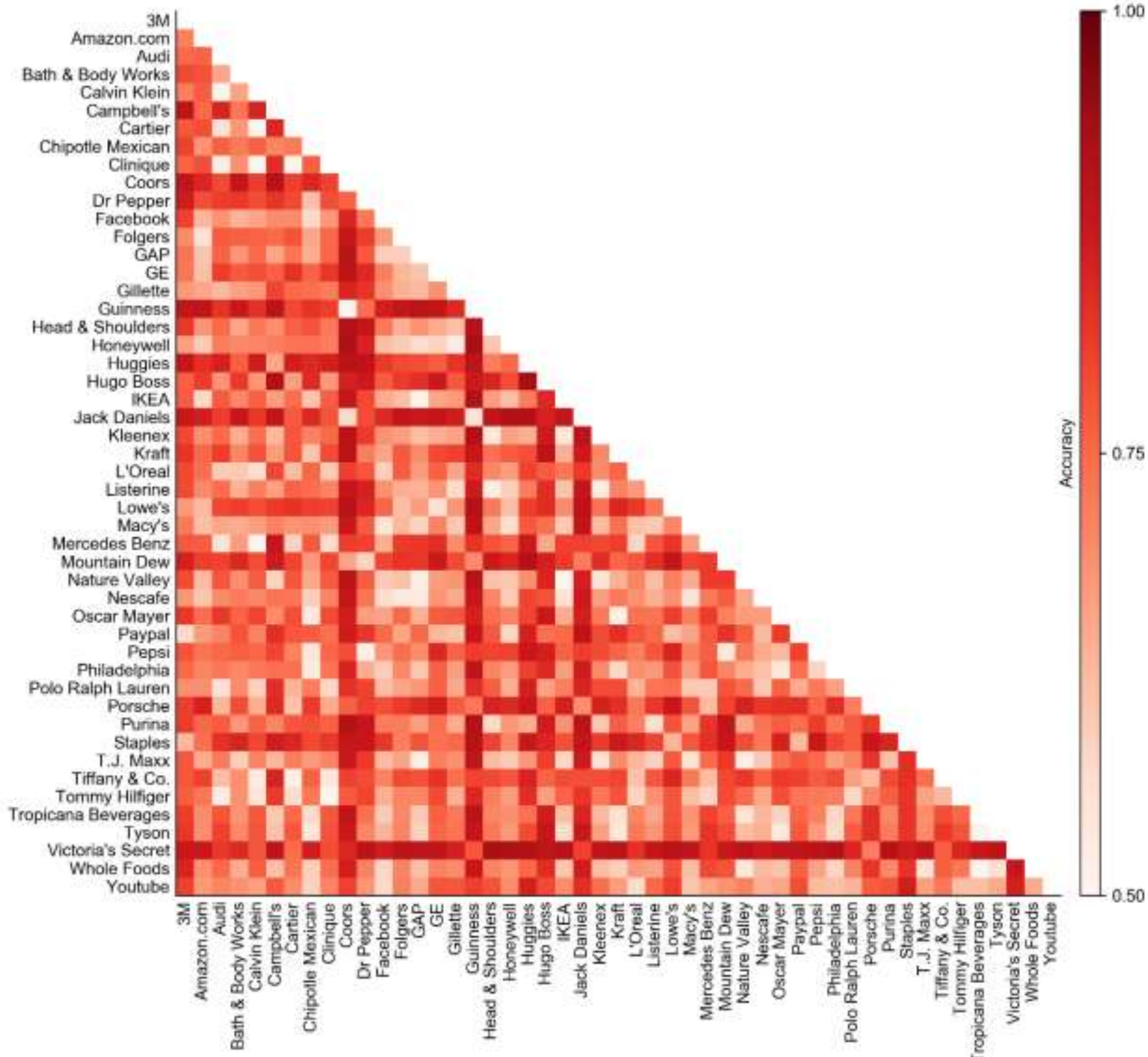
Place	**Person**
Related to 'familial':	
basement, bathroom, fireplace, home, house, household, kitchen, nursery, restroom, shower	baby, child, dad, daughter, family, father, grandmother, grandparent, housewife, mom, mom, mother, parent, sister, toddler
Related to 'professional':	
bank, boardroom, business, campus, class, classroom, clinic, college, court, lab, library, office, pharmacy, school, workplace	actor, artist, associate, athlete, athletic, baker, banker, bartender, blogger, builder, bullfighter, businessman, buyer, cashier, cleaner, contractor, cop, creator, dentist, designer, doctor, driver, employee, executive, farmer, graduate, lumberjack, maid, manager, nurse, owner, pharmacist, photographer, pilot, salesperson, student, workaholic, worker
Related to 'communal':	
arena, ballroom, bar, beach, brewery, cafe, cafeteria, club, concert, dorm, event, festival, gala, garden, golf, gym, hall, hallway, hotel, lobby, lounge, mall, park, playground, pool, prom, pub, restaurant, skatepark, stadium, vacation	buddy, cheerleader, comrade, frat, friend
Related to 'intimate':	
bedroom, resort, wedding	babe, couple, cutesy, husband, lover, wife
Other:	
airport, aisle, America, Angeles, apartment, area, backyard, base, center, Chipotle, city, cliff, Costco, country, depot, desert, destination, doorstep, earth, environment, Europe, factory, farm, field, forest, front, garage, ghetto, Greece, highway, hill, hospital, indoor, Italy, jungle, KFC, lake, Manilla, McDonalds, Milan, mountain, nature, NYC, ocean, outdoor, outside, place, room, runway, Safeway, salon, showroom, side, sidewalk, site, sky, space, stage, Starbucks, station, store, street, studio, suburb, suburbia, subway, supermarket, theater, track, tram, valley, Walgreens, Walmart, warehouse, wonderland, Woodstock, yard, zoo	adolescent, adult, American, anybody, anyone, boy, brunette, celebrity, chick, citizen, climber, coed, consumer, customer, Daniel, daredevil, drinker, dweller, eater, elder, entertainer, everyone, fan, female, folk, foodie, gamer, geek, German, girl, guy, hick, hiker, hipster, homeless, Hugo, icon, infant, Italian, joe, kid, king, lackey, lady, LeBron, loser, Louis, male, man, millennial, minority, nerd, people, person, player, poser, rapper, redneck, rockstar, runner, Sam, shopper, skateboarder, skater, sportsman, squad, stoner, supermodel, supporter, techie, teen, teenager, traveler, watcher, woman, youth

(B) Scale rating

We randomly chose a subset of 49 major American consumer brands from the larger pool of 157 brands. Eighty participants, in return for a payment of US$0.80, rated each of the 49 brands based on how closely the brand fitted each of the four words: ‘work’, ‘lust’, ‘family’, and ‘party’, respectively using unmarked visual analog scales (i.e., the same brand perception task described in Study 1). The correlations between the four scores range from -.023 to .278, with the exception of communal-intimate (.576).

Based on the four scores for each brand from all participants, we conducted a leave-one-subject-out (LOSO) pairwise brand classification test using support vector machine algorithm. Of the 1,176 unique pairwise brand classifications, the average LOSO cross-validated classification accuracy was 73.9% (S.D. = 9.9%), significantly above 50% chance level (t = 82.6, p < .001). Moreover, when any one of the context scores was removed from brand classification, accuracy worsened significantly (70.3% – 72.4%, ts = 15.5 – 26.0, all ps < .001). The findings offer further supportive evidence that each of the four social contexts contains unique information about brand image.

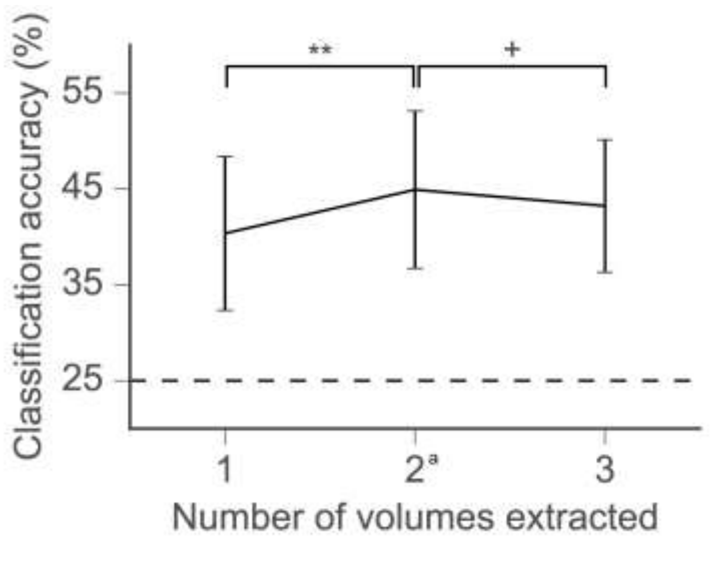
Figure S1. Leave-one-subject-out cross-validated classification accuracy between brands using the four social context scores obtained in an online survey (N = 80)



Supplementary Analysis 2: Determining Number of Volumes in Picture Viewing Task

We attempted to determine the optimal number of volumes (TR = 2.3s) to be extracted during picture viewing task (7s), using the classification accuracy of the four contexts as benchmark. Paired *t*-tests of within-subject classification accuracies were conducted. We found that using two volumes (4.6s) instead of one (2.3s) or three (6.9s) produced the best social context classification accuracy.

Figure S2. Social context classification accuracies with varying numbers of volumes extracted in picture viewing task

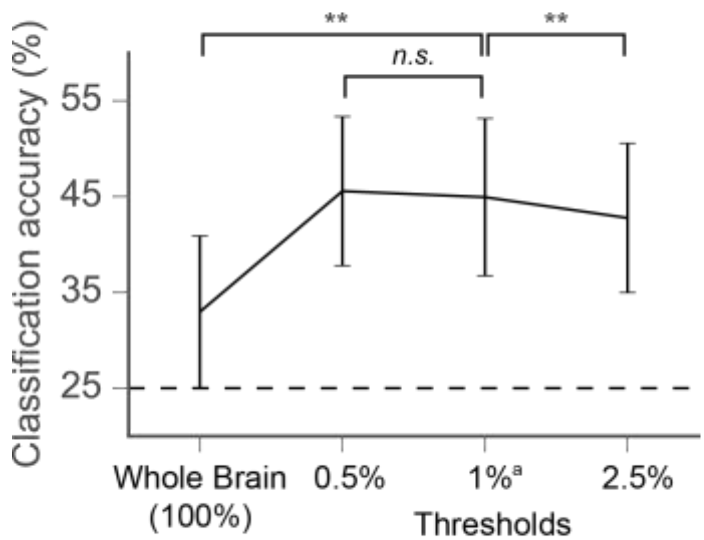


+ $p < .10$; ** $p < .01$; [a] Results reported in the main analysis

Supplementary Analysis 3: Determining Number of Voxels in Picture Viewing Task

To investigate whether voxel selection is a necessary step, we compared the social-context classification accuracy using the entire brain (58682 voxels) to that of using ROI masks based on different thresholds (0.5%, 1708 voxels; 1%, 3173 voxels; 2.5%, 7125 voxels). Paired *t*-tests of within-subject classification accuracies were conducted. We found that, in general, voxel selection improved social context classification accuracy.

Figure S3. Social-context classification accuracies with varying numbers of voxels extracted in picture viewing task



+ $p < .10$; ** $p < .01$; [a] Results reported in the main analysis

Supplementary Analysis 4: Robustness to Varying Number of Volumes in Brand Imagery Task

We varied the number of volumes extracted in brand imagery task (total length 11s, consisting of 2s brand logo, 2s cue, followed by 7s visualization), by using either one volume at brand logo onset (adding 6s to account for hemodynamic delay) or the average of two or four consecutive volumes after brand logo onset. Findings reported in the main analysis were robust to this manipulation.

Table S3. Analysis results based on different numbers of volumes in brand imagery task

Volumes extracted from brand logo onset[b]	1	2	3[a]	4
Spanning length (s)	2.3	4.6	6.9	9.2
F-statistic of fixed effect of neural context scores on self-report brand perceptions (c.f. H_1)	9.7**	13.2***	15.7***	9.7**
Average correlation between neurally- and self-report brand dissimilarity matrices (c.f. H_2)	.086***	.101***	.107***	.097***
Correlation between inter-brand neural profile disparity and co-branding suitability (c.f. H_3)	-.369***	-.404***	-.384***	-.371***
Correlation between inter-subject neural profile disparity and brand image strength (c.f. H_4)	-.555*	-.566*	-.627*	-.533*

* $p < .05$; *** $p < .001$; [a] Results reported in the main analysis; [b] Added 6s to account for hemodynamic delay

Supplementary Analysis 5: Robustness to Varying Number of Voxels in Brand Imagery Task

In relation to Supplementary Analysis 3, we recalculated key statistics with varying voxel selection thresholds (0.5% and 2.5%). Findings reported in the main analysis (1% threshold) were robust to this manipulation.

Table S4. Analysis results based on different voxel selection thresholds

Threshold	0.5%	1%[a]	2.5%
Voxel size of ROI mask	1708	3173	7125
Picture category classification accuracy (%)	45.6***	44.9***	42.8***
(SD)	(7.8)	(8.2)	(7.8)
F-statistic of fixed effect of neural context scores on self-report brand perceptions (c.f. H_1)	16.7***	15.7***	14.34***
Average correlation between neurally- and self-report brand dissimilarity matrices (c.f. H_2)	.108***	.107***	.093***
Correlation between inter-brand neural profile disparity and co-branding suitability (c.f. H_3)	-.380***	-.384***	-.381***
Correlation between inter-subject neural profile disparity and brand image strength (c.f. H_4)	-.638*	-.627*	-.560*

* $p < .05$; *** $p < .001$; [a] Results reported in the main analysis

Supplementary Analysis 6: Robustness to Excluding Visual Cortex

To investigate whether the results were driven mainly by visual processing of physical features of the stimuli, we excluded voxels from the occipital lobe using the Automated Anatomical Labeling (AAL) atlas. Findings reported in the main analysis were largely robust to this manipulation.

Table S5. Analysis results based on exclusion of visual cortex

Excluding visual cortex	No[a]	Yes
Voxel size of ROI mask	3173	1930
Picture category classification accuracy (%) (SD)	44.9*** (8.2)	40.8*** (7.6)
F-statistic of fixed effect of neural context scores on self-report brand perceptions (c.f. H_1)	15.7***	15.02***
Average correlation between neurally- and self-report brand dissimilarity matrices (c.f. H_2)	.107***	.082***
Correlation between inter-brand neural profile disparity and co-branding suitability (c.f. H_3)	-.384***	-.334***
Correlation between inter-subject neural profile disparity and brand image strength (c.f. H_4)	-.627*	-.474+

+ $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$; [a] Results reported in the main analysis

Supplementary Analysis 7: Robustness to Using Alternative Signal Extraction Method

Instead of averaging raw voxel signals across volumes, we used an alternative method to extract neural data from the brain images. Specifically, for each participant we used a first-level fixed-effect general linear model (GLM) to estimate parameters (beta images) for each of the 112 pictures in the picture viewing task using a box-car regressor of 7s, and separately for each of the 14 brands in the brand imagery task using a box-car regressor of 11s (2s brand logo + 2s cue + 7s imagery). We then re-conducted the analysis with these beta images and found that the results were replicated.

Table S6. Analysis results based on beta images

Extraction method	Raw voxel data[a]	Parameter estimates from GLM
Picture category classification accuracy (%) (SD)	44.9*** (8.2)	52.8*** (6.9)
F-statistic of fixed effect of neural context scores on self-report brand perceptions (c.f. H_1)	15.7***	21.6***
Average correlation between neurally- and self-report brand dissimilarity matrices (c.f. H_2)	.107***	.069**
Correlation between inter-brand neural profile disparity and co-branding suitability (c.f. H_3)	-.384***	-.377***
Correlation between inter-subject neural profile disparity and brand image strength (c.f. H_4)	-.627*	-.547*

$^+$ $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$; [a] Results reported in the main analysis

Supplementary Analysis 8: Robustness to Using Native Brain Space and Individual Masks

We used untransformed images in each participant's native brain space and created individually-calibrated ROI masks (i.e., selecting voxels based on the participant's own contrast maps instead of the group's). Findings reported in the main analysis were largely robust to this manipulation.

Table S7. Analysis results based on different numbers of volumes in brand imagery task

Brain image space Voxel size of ROI mask	MNI normalized[a] 3173	Native 3697 – 5469
Picture category classification accuracy (%) (SD)	44.9*** (8.2)	47.2*** (8.8)
F-statistic of fixed effect of neural context scores on self-report brand perceptions (c.f. H_1)	15.7***	12.8***
Average correlation between neurally- and self-report brand dissimilarity matrices (c.f. H_2)	.107***	.084***
Correlation between inter-brand neural profile disparity and co-branding suitability (c.f. H_3)	-.384***	-.381***
Correlation between inter-subject neural profile disparity and brand image strength (c.f. H_4)	-.627*	-.411

* $p < .05$; ** $p < .01$; *** $p < .001$; [a]Results reported in the main analysis

Supplementary Analysis 9: Robustness of Neural Profiles to Subsampling of Pictures

We examined the robustness of neural profiles by subsampling the 112 pictures, using only a subset of them to calculate neural profile disparity between brands. We first conducted random subsampling (repeated 1,000 times) of 75%, 50%, and 25% of the pictures, and then excluded 25% of the pictures by each picture category. Correlations with external ratings were shown to be largely robust to both procedures.

Table S8. Correlations between inter-brand neural profile disparity and co-branding suitability (c.f. H_3) after picture subsampling

Subsampling of pictures		Random subsampling (N = 1000)		
	100%[a]	75%	50%	25%
Correlation between inter-brand neural profile disparity and co-branding suitability (c.f. H_3) (SD)	-.384***	-.384*** (.007)	-.381*** (.012)	-.376*** (.021)
Correlation between inter-subject neural profile disparity and brand image strength (c.f. H_4) (SD)	-.627*	-.614* (.045)	-.585* (.079)	-.518[+] (.125)

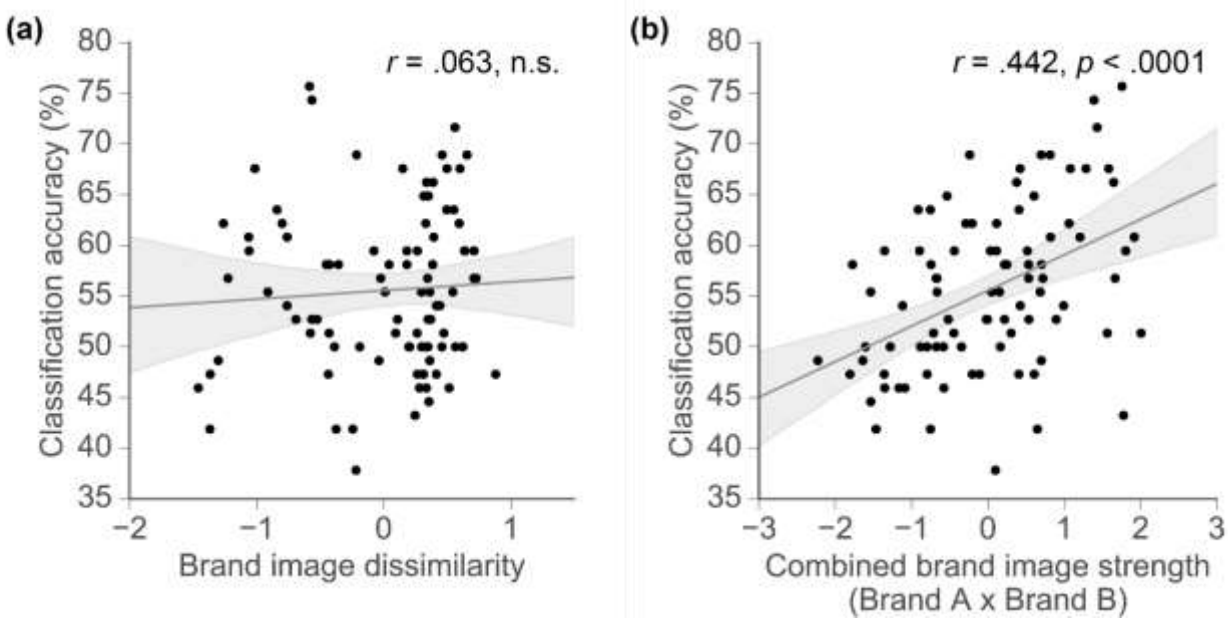
Subsampling of pictures		Excluding category			
	100%[a]	Familial	Communal	Intimate	Professional
Correlation between inter-brand neural profile disparity and co-branding suitability (c.f. H_3)	-.384***	-.380***	-.383***	-.390***	-.379***
Correlation between inter-subject neural profile disparity and brand image strength (c.f. H_4)	-.627*	-.635*	-.511[+]	-.362	-.717**

[+] $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$; [a] Results reported in the main analysis

Supplementary Analysis 10: Brand Identification Based on Neural Profiles

We explored whether neural profiles of brand image obtained from the participants could be used to identify brands they were watching inside scanner. We performed 91 pairwise leave-one-subject-out cross-validation classification tests using linear support vector machine (SVM), obtaining classification accuracies between all pairs of 14 brands. Average classification accuracy was 55.5% (SD = 7.9%; significantly above 50% chance, $t = 6.65$, $p < .0001$). We also wanted to know whether brand image dissimilarity or strength modulates classification accuracy rate. Averaged perceived brand image similarity (how different two brands are perceived by participants in the neural sample) did not correlate with classification accuracy ($r = .063$, n.s., Figure S3a). Combined brand image strength (the multiplication product of two brands' image strengths evaluated by external raters), however, correlated with classification accuracy ($r = .442$, $p < .0001$, Figure S3b). The findings provide further evidence that brand image strength is related to brand image consistency, since cross-subject classification relies in part on the fact that participants produced similar neural profiles for the same brand.

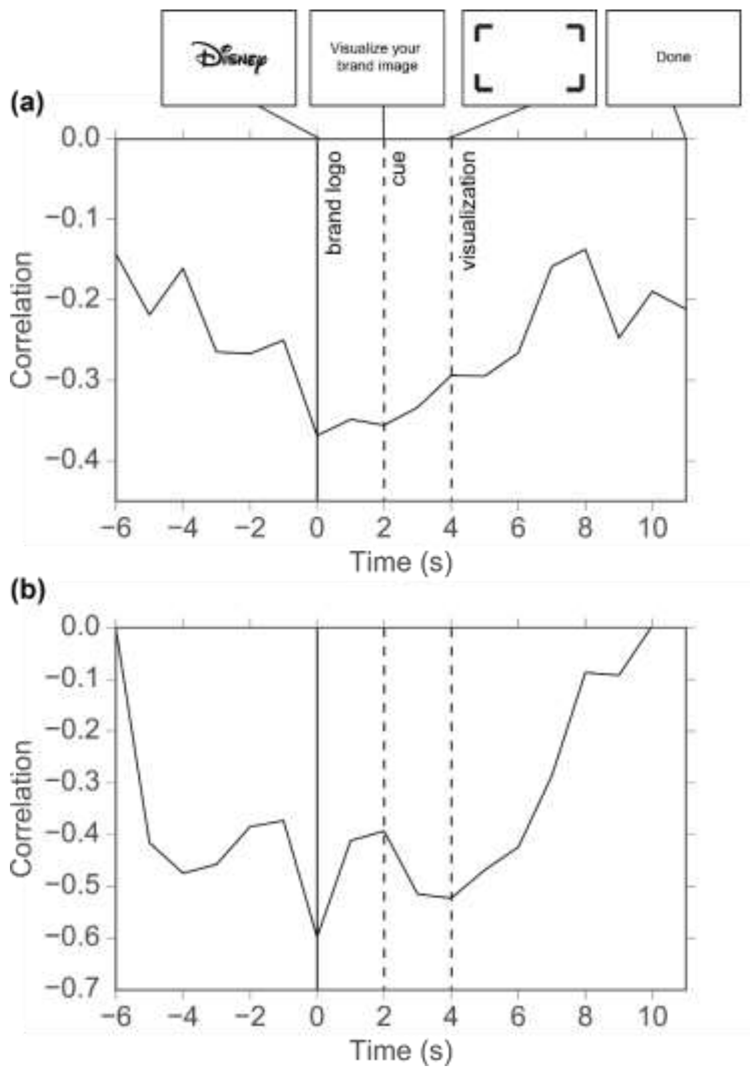
Figure S4. Correlation between classification accuracy and (a) self-report brand image dissimilarity and (b) combined brand image strength



Supplementary Analysis 11: Temporal Specificity of Neural Profiles

We explored to what extent the neural profiles obtained from the analysis were temporally specific to the task, i.e., whether they were time-locked to the onset of brand logo and visualization period. We reconstructed neural profiles using brain responses collected at different time points, from before brand logo onset (-6s) to after the end of visualization period (+11s) at 1s intervals (after accounting for 6s delay in hemodynamic response), and recomputed statistical measures in H_3 and H_4. Both measures reached the largest magnitude around brand logo onset, offering support to the temporal specificity of neural profiles.

Figure S5. Time series plots of (a) correlation between inter-brand neural profile disparity and cobranding suitability (c.f. H_3) and (b) correlation between inter-subject neural profile disparity and brand image strength (c.f. H_4). Time axis is shifted 6s rightward to account for hemodynamic response.



Supplementary Analysis 12: Predicting Brand Image Strength by Self-Report Data

We explored whether self-report brand perception data from the Study 1 sample could also predict brand image strength using the following procedure: For each brand, we collected the four self-report brand perception scores (‘work’, ‘lust’, ‘family’, and ‘party’) from 37 participants, and then calculated the average inter-subject pairwise correlational distance from those self-report responses. This self-report data consistency score from Study 1 participants does not correlate with brand image strength (r = .147, n.s.).

Supplementary Analysis 13: Predicting Co-Branding Suitability by Self-Report Data

We first averaged the 37 participants' matrices of self-report brand image dissimilarity and inter-brand neural profile disparity. In the regression analysis with co-branding suitability of 91 brand pairs as the dependent variable, we found that self-report data explained a large proportion of the variance in co-branding suitability. We then explored the relative strengths of self-report and neural data in predicting externally rated co-branding suitability. Adding neural data did not increase the explained variance of the model.

Table S9. Regression models with co-branding suitability of 91 brand pairs as dependent variable

Model	1	2	3
Group-averaged self-report brand image dissimilarity	-.880***		-.866***
Group-averaged inter-brand neural profile disparity		-.384***	-.034
R^2	.774	.148	.775
ΔR^2 (Model 1 to 3)			.001
ΔR^2 (Model 2 to 3)			.627***

* $p < .05$; ** $p < .01$; *** $p < .001$

Supplementary References

Barton, Kamil (2016), "Multi-Model Inference," [available at https://cran.r-project.org/web/packages/MuMIn].

Bates, Douglas, Martin Mächler, Benjamin M. Bolker, and Steven C. Walker (2015), "Fitting linear mixed-effects models using lme4," *Journal of Statistical Software,* 67 (1), 1–48.

Fellbaum, Christiane (1998), *WordNet*, Wiley Online Library.

Hanke, Michael, Yaroslav O. Halchenko, Per B Sederberg, Emanuele Olivetti, Ingo Fründ, Jochem W Rieger, Christoph S Herrmann, James V. Haxby, Stephen José Hanson, and Stefan Pollmann (2009), "PyMVPA: A Unifying Approach to the Analysis of Neuroscientific Data.," *Frontiers in neuroinformatics,* 3 (February), 3.

Singmann, Henrik, Benjamin M. Bolker, Mikko Viinikainen, Frederik Aust, Søren Højsgaard, John Fox, Michael A. Lawrence, and Ulf Mertens (2016), "Analysis of Factorial Experiments," [available at https://github.com/singmann/afex].