

HANG-YEE CHAN

Decoding the consumer's brain

Neural representations of consumer experience



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Het ontcijferen van het consumentenbrein

Neurale representaties van consumentenervaringen

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Chapter 1

Introduction

Understanding consumer experience – what consumers think about brands, how they feel about services, whether they like certain products – is crucial to marketing practitioners since it helps them forecast market demands, improve existing offerings or uncover emerging trends. In the realm of academic research, having access to consumers' thoughts and feelings is equally essential to theory generation and testing.

The promise of understanding consumers' mind by probing their brains directly has generated excitement on both the practice and theory fronts. 'Neuromarketing', as the application of neuroscience in marketing research is called (Smidts, 2002), ignites the imagination of many who see the potential of extracting neural information from consumers. While traditional sources of information used in marketing such as self-report instruments remain indispensable, measurement at the brain level could offer several advantages over conventional methods: First, real-time observation eliminates memory error or recall bias that is common in retrospective reporting (MacKenzie & Podsakoff, 2012). Unobtrusive, continuous recording also makes possible dynamic tracking of an immersive experience, such as watching a movie or browsing on a website. Moreover, mental processes that do not arise to consciousness can potentially be made observable.

Several neuroimaging techniques – such as electroencephalogram (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging

(fMRI) – are particularly apt for consumer neuroscience research given their non-invasiveness and suitable spatiotemporal resolution. Not surprisingly, as these methods become less expensive and more accessible, their application has become more widespread, as can be attested by the growing number of academic publications and neuromarketing firms (Plassmann, Ramsøy, & Milosavljevic, 2012).

For the purpose of this dissertation, I will equate ‘consumer neuroscience’ and ‘neuromarketing’ as the application of neuroscience in the academic research of marketing. Where commercial practices of neuromarketing research is referred to, the distinction will be explicitly mentioned.

1.1 Use of neuroimaging in marketing research

As a relatively nascent subfield in marketing research, consumer neuroscience has seen substantial expansion both in terms of breadth and depth, as documented by several review papers (Ariely & Berns, 2010; Plassmann et al., 2012; Plassmann, Venkatraman, Huettel, & Yoon, 2015; Smidts et al., 2014). It is not the aim here to provide an exhaustive overview of the state of the art; instead, I will highlight key themes among studies that have used neuroimaging methods in marketing research.

While commercial firms practicing neuromarketing predominantly prefer EEG given its high temporal resolution and affordability, fMRI is an equally, if not more, common technique in academic consumer neuroscience research. With this imaging method, blood oxygenation level dependent (BOLD) signals in the brain are recorded while participants engage in various types of tasks. While its temporal resolution (~0.5Hz) is inferior to that of EEG (>1000Hz), its ability to provide relatively high spatial accuracy (in cubic millimeters) and access to subcortical structures means that it is possible to use imaging data to locate neural substrates of mental processes.

In vastly simplified terms, a typical fMRI study would compare consumers' brain activities in one condition to another (e.g., viewing favorite versus non-favorite brand logos), thereby creating pair-wise contrasts of neural activations among different conditions. By comparing voxels (volumetric unit of a brain image) one by one, researchers can identify brain regions associated with certain mental processes relevant to marketing (e.g., brand preference).

Location-based analysis of fMRI recordings has contributed substantially in marketing research, most importantly in two aspects: understanding mental processes and improving market predictions.

1.1.1 Understanding mental processes

Consumer behavior is usually driven by complex cognitive processes involving attention, emotion, memory and valuation. From early on, studies in consumer neuroscience have attempted to locate brain areas involved in these processes within the marketing context. Numerous studies with participants evaluating consumer products and brands during fMRI scanning have found that nucleus accumbens (NAcc), ventral medial prefrontal cortex (vmPFC) and dorsolateral prefrontal cortex (dlPFC) contain information about the consumer's expected utility. For example, activation at NAcc is associated with expected rewards of money or products (Knutson, Rick, Wimmer, Prelec, & Loewenstein, 2007; Knutson et al., 2008) and celebrity endorsements (Klucharev, Smidts, & Fernández, 2008), while brand preference can be linked to increased activity at vmPFC and decreased activity at dlPFC (Deppe, Schwindt, Kugel, Plassmann, & Kenning, 2005). On the other hand, experienced value, such as pleasures from smell, sound and sight, coincides with the activation of medial orbitofrontal cortex (mOFC; Berridge & Kringelbach, 2015).

While knowing where in the brain mental processes take place may not be of primary interest to marketing researchers, they do provide building blocks for subsequent studies to delineate the psychological mechanism during

consumer decision-making. For example, a study on social influence found that when people's own view conflicts with the group consensus, the degree to which they later conform and revise their judgment is associated with activation at the rostral cingulate zone (RCZ) and NAcc during the conflict (Klucharev, Hytönen, Rijpkema, Smidts, & Fernández, 2009). Since preceding studies have shown that RCZ and NAcc are recruited in reinforcement learning tasks, the comparable findings obtained in the social context suggest that group norms evoke conformity via similar learning mechanisms.

In another example, Plassmann and colleagues (2008) scanned participants' brains while they tasted identical wines with different price tags. They found that increasing the price of wine altered the activation at mOFC during the actual wine tasting. As past neuroscientific literature has demonstrated the relationship between mOFC and sensory pleasantness, the authors argue that marketing actions alter not only the expected value of a product, but also the experienced value during its consumption.

While this approach produces insights on the psychological mechanism of consumer experience, it does at the same time pose the issue of reverse inference, i.e., the presence of brain activation at a particular location is inferred as the engagement of a specific mental process (Poldrack, 2006). The problem is that since the brain is a complex system, rarely is there one-to-one correspondence between a mental process and a brain region. For example, medial prefrontal cortex (mPFC) and precuneus are associated with both processing rewards (Bartra, McGuire, & Kable, 2013) and mentalizing (Frith & Frith, 2006). Thus, a study that shows high-status car brands activated mPFC and precuneus (Schaefer, Berens, Heinze, & Rotte, 2006) cannot conclusively tell whether high-status brands evoke reward processing or self-reflection (or yet other mental processes associated with these regions). However, this issue can be addressed in part by weighing evidence through large-scale automated meta-analysis (Yarkoni, Poldrack, Nichols, Van Essen, & Wager, 2011) or even bypassed in some cases, such as Yoon and associates

(2006) who set out to test whether brands are indeed evaluated as persons; by comparing brain activations between person- and brand-judging tasks, they provide evidence refuting the view that processing of products and brands is akin to that of humans.

1.1.2 Improving market predictions

Forecasting market outcomes is another important task in marketing. As location-based analysis builds the bridge between brain and behavior by matching the latter to the former, more recent studies begin to flip the equation and try to predict behavioral outcomes based on neural activity. Numerous studies link neural activity to subsequent purchase behavior (Knutson et al., 2007; Levy & Glimcher, 2012; Plassmann, O'Doherty, & Rangel, 2007). In some sense, reading out a person's brain responses when they encounter various products is akin to obtaining their self-report ratings or observing their choices in traditional marketing research. The theoretical questions that follow then are: (a) Does neural information gathered in a small group of people (so-called 'neural focus group') predict aggregate choices in the market? (b) Does this neural information provide non-redundant signals compared to what can be obtained by conventional – and often considerably less expensive – behavioral measures?

In a review paper, Knutson and Genevsky (2018) offer early affirmative evidence to both questions. Activation at NAcc and vmPFC measured in a small group of participants – brain areas traditionally associated with reward processing – correlate with various aggregate outcomes in the market (such as song downloads, ad responses, content shares, etc.). Moreover, a number of studies have shown that neural information improve the prediction of market outcomes using behavioral measures obtained from the same group (Berns & Moore, 2012; Boksem & Smidts, 2015; Genevsky & Knutson, 2015; Genevsky, Yoon, & Knutson, 2017; Venkatraman et al., 2015), showing that there is hidden information in the brain that is not completely uncovered by self-report preference or observable choice alone. Given the right cost-benefit

case, this brain-as-predictor approach (Berkman & Falk, 2013) may potentially add value to existing marketing strategies.

1.1.3 Limitation of location-based neuroimaging analysis

A large majority of existing consumer neuroscience studies, either mapping brain regions to mental processes or using neural activation to predict behavior, treat neural information as a unidimensional construct. A brain region is either turned on or off when a mental process is involved; the intensity of activation at a certain brain region tracks with some external measures such as self-report preference or sales. Such a unidimensional approach, however, has its limitations.

First, information is not necessarily encoded in a single site. Subjective value, for example, is found to be encoded in various brain regions beyond NAcc and vmPFC, such as thalamus, precuneus, and anterior cingulate cortex (Bartra et al., 2013). Moreover, information may not be encoded in the form of isolated pockets of activations, but of correlated activities across a network of brain areas. As another example, a series of studies have shown that exercising self-control does not only manifest in increased dlPFC activation, but also in the strengthening of connectivity between dlPFC and vmPFC (Hare, Camerer, & Rangel, 2009; Hare, Hakimi, & Rangel, 2014).

Second, some of the psychological constructs pertinent to marketing cannot be neatly mapped onto a unipolar variable that tracks with activation intensity. Consider emotion as an example. A marketer may want to know how consumers emotionally react during consumption. While a self-report instrument can ask consumers to respond to an array of emotional labels, the presence or absence of a given emotion is seldomly attributable to the activation of a particular brain region (Barrett & Wager, 2006; Hamann, 2012; Nummenmaa & Saarimäki, 2019). In addition, the problem of reverse inference as discussed before made such one-to-one mapping between activation at a certain area and the occurrence of an emotion difficult.

Third, and perhaps most importantly, marketers are not exclusively concerned with consumer attitude, but also consumer experience. In other words, while it is good to know whether consumers like a brand (yes or no), it is equally if not more important to know what consumers think about it ('cool', 'trendy', 'boring', etc.). Being able to infer mental content based on neural activations would provide invaluable insights for marketing practitioners and researchers alike. In the next sections, I will first discuss the hurdles of measuring consumer experience using conventional methods, and then introduce recent advances in neuroimaging analysis that can help consumer neuroscience researchers achieve such goal through brain measurements.

1.2 Measuring consumer experience

Experience encompasses sensations, emotions, cognitions and behavioral responses (Holbrook & Hirschman, 1982; Schmitt, 1999). Consumer experience occurs when consumers seek and examine products; when they shop for products or receive service; and when they consume and use the products (Brakus, Schmitt, & Zarantonello, 2009). It is in contrast with other marketing constructs such as belief ('I think the quality is good') and satisfaction ('I like it'), of which consumer experience is often the antecedent.

Marketing practitioners have long recognized the importance of consumer experience and championed for a more systematic approach to its creation and management (Pine & Gilmore, 1998; Shaw & Ivens, 2002). They point to the success of Starbucks, for example, to argue that it is not only the quality of the focal product (coffee) but also the interactions with staff and shop atmospherics that create better value propositions for customers (Michelli, 2006). At the same time, academic research in this area is still in its early stage (Gentile, Spiller, & Noci, 2007; Homburg, Jozić, & Kuehnl, 2017; Puccinelli et al., 2009), with efforts to formalize and conceptualize

consumer experience in various contexts, such as retailing, service, customer relations, and branding.

The phenomenological nature of experience means that what is being studied involves non-verbal sensations and unfolds over time. This poses a problem in measurement, since it is hard to quantify and collate qualitative phenomena. Attempts to measure consumer experience through self-report focus on capturing different *attributes* of such experience (Brakus et al., 2009; Gentile et al., 2007; Varshneya & Das, 2017). For example, a scale constructed by Brakus and colleagues (2009) focuses on the brand's ability to evoke various aspects of consumer experience (an example item is 'This brand includes feelings and sentiments'). What exact feelings and sentiments a brand could evoke, however, were left unexplored.

The hurdles of measuring consumer experience through traditional methods are multiple; chief among them are:

Experience is difficult to access. Consumers immersed in an experience are often not in a controlled and deliberative state of mind, and do not have access to nonconscious mental processes. For example, in an evaluative conditioning experiment (Sweldens, Van Osselaer, & Janiszewski, 2010), consumers asked to watch a series of images paired with brands changed their brand preference afterwards without self-report awareness. Methods such as the Implicit Association Test (Greenwald, McGhee, & Schwartz, 1998) help reveal only a limited sliver of implicit beliefs and associations since they require elaborate and pre-defined calibration. Moreover, many instances of consumer experience – seeing a concert, watching a movie, or interacting with frontline staff in a shop – unfold over time. The ephemeral nature makes real-time, in-the-moment measurement difficult. As a result, apart from self-report, many methods of continuous measurement have been used in marketing research, such as affect rating dial (Ruef & Levenson, 2007), computerized facial coding (Lewinski, Fransen, & Tan, 2014), and eye-tracking (Teixeira, Wedel, & Pieters, 2012). Each of these methods taps onto

observable physiological or behavioral responses during an ongoing experience, based on which the quality of such experience is inferred, such as attention or affect.

Experience is difficult to verbalize. Even when consumers have conscious access to the experience, it may be hard for them to articulate. For example, sensory experiences involving taste, smell and touch are difficult to put into words. Complex and abstract inner thoughts, such as brand image, are also hard to verbalize. One way to solve this problem is to impose a pre-defined framework onto the study of experience, for example turning brand image into a predefined set of personality attributes (J. Aaker, 1997). It should be noted, however, that the usefulness of any organizational scheme depends highly on the context (e.g., any existing data collected with a brand personality scale will be of little use if one wants to study, say, visual associations of brands). On the other hand, there exist qualitative methods such as imagery elicitation (Roth, 1994) and structured interviews (Fournier, 1998) that offer rich first-person accounts. Alternative methods, such as free association (Krishnan, 1996) and concept mapping (John, Loken, Kim, & Monga, 2006) have been developed to assist consumers to report their mental associations. Nonetheless, the translation from thoughts and feelings to words is still a potential bottleneck in the measurement of consumer experience.

1.3 Moving beyond location-based fMRI analysis

For consumer neuroscientists who aim to meet the challenge of understanding consumer experience, recent methodological advances in analyzing neuroimaging data open new possibilities to accessing the content of human thoughts. Multivariate pattern analysis (MVPA; Haxby et al., 2001; Norman, Polyn, Detre, & Haxby, 2006; O'Toole et al., 2007) moves beyond single voxel activation and focuses on finding activation patterns in a subset of voxels. In other words, instead of looking for signal in the intensity

level of a particular voxel, researchers attempt to uncover a reliable configuration of intensities across multiple voxels using pattern-classification techniques. Effectively, the MVPA approach aims to uncover stable spatial or temporal (or both) representations from neuroimaging data that can be associated with certain mental phenomena.

MVPA pools information from multiple voxels at one time, making it potentially more sensitive in detecting neural activities and their statistical associations with (and predictive power of) complex mental phenomena, such as semantic or affective processing. To illustrate, consider the classic example of a person viewing images of either faces, houses or objects. In an early neuroimaging study using the conventional approach, pairwise comparisons of brain activation levels under these conditions yielded the finding that on average, the lateral temporal region displayed stronger activations when viewing objects (Ishai, Ungerleider, Martin, Schouten, & Haxby, 1999). However, it was not possible to know exactly which object the person was viewing simply based on the average activation *level* of a brain region. In a later study, the activation *pattern* of the ventral temporal region (i.e., activation level at each voxel within the area that encompasses all the brain regions mentioned above) was analyzed as a whole. Employing supervised machine learning algorithms, the same researchers were then able to perform multi-category classification and predict above chance whether a person was viewing pictures of, for example, bottles, shoes, or scissors (Haxby et al., 2001). Since this seminal study on decoding mental content based on neural response patterns, MVPA has been evolving quickly and at the same time gaining popularity among neuroscientists. In consumer neuroscience research, however, the application of MVPA has been limited so far (see, e.g., Y.-P. Chen, Nelson, & Hsu, 2015; Grosenick, Klingenberg, Katovich, Knutson, & Taylor, 2013; Hakim & Levy, 2019).

By using machine learning and pattern similarity analysis, patterns of neural activations associated with certain consumer experience can be extracted, analyzed and interpreted. Here I first briefly describe three common MVPA

methods, which are closely related with each other: pattern classification, representational similarity, and inter-subject correlation (see Figure 1.1 for overview).

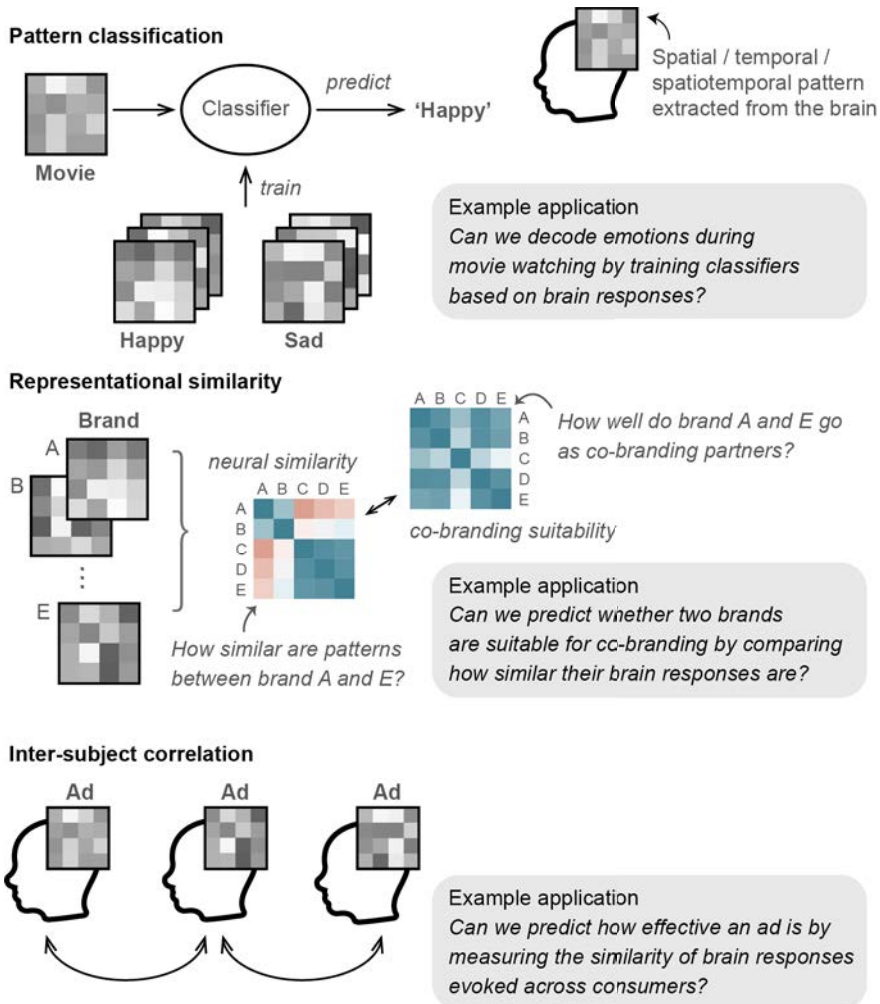


Figure 1.1 Various MVPA methods and potential applications in marketing research

Pattern classification. Early MVPA studies have observed that brains engaging in certain states produce stable spatial patterns of neural activations. That gives rise to the idea of ‘mind reading’ based on brain measurements, which is basically an implementation of supervised machine learning (Norman et

al., 2006). Neuroimaging data are organized into a training set and a testing set. A classifier is trained based on the training data (brain responses triggered in certain conditions, such as looking at face versus house pictures). The trained classifier is then used to predict condition labels of testing data, i.e., such that one can determine, based on a given neural response pattern, whether a person is looking at a picture of a face or of a house.

In the same vein, to the extent affective states are encoded in stable spatial patterns, it is possible to infer them based on brain measurements. Can we therefore build a classifier that can differentiate unique representations of emotional states, such as happy and sad (Saarimäki et al., 2016)? If so, can we ‘decode’ moment-by-moment emotional responses when a consumer watches, say, a TV commercial?

Representational similarity. Representational similarity analysis (RSA) is a form of multivariate pattern analysis which is able to characterize brain regions by their representational similarity, computed in the form of a distance matrix of response patterns (Charest & Kriegeskorte, 2015). The assumption is that pattern similarity of two neural representations (e.g., a picture of dog and a picture of cat) can indicate the conceptual similarity of these representations (both are animals). The technique was first applied in the study of object recognition in the visual cortex. However, recently, this method has been expanded to study more abstract mental activities, such as semantic processing (Clarke & Tyler, 2014).

Does representational similarity of neural responses carry behavioral implications? Extant literature on co-branding and brand alliance emphasizes the importance of perceptual fit (Gammoh, Voss, & Chakraborty, 2006; Simonin & Ruth, 1998; Thompson & Strutton, 2012) in determining the success of such endeavors. A relevant question for marketing would be whether we can predict if two brands are suitable co-branding partners by comparing how similar the neural patterns evoked by them.

Inter-subject correlation. The technique is built on the notion that people experiencing similar subjective phenomena will exhibit comparable brain responses. Group-level similarity in brain response patterns, for example synchronized temporal neural changes across individuals during video-watching, has been shown to be a sign of a captivating experience that draws attention (Nastase, Gazzola, Hasson, & Keysers, 2019). In particular, inter-subject correlation is found to increase when stimuli are of high arousal or negative valence levels (Nummenmaa et al., 2012). This group-level measure can be used to demonstrate commonality of mental processing among individuals.

In the domain of consumer neuroscience, whole-brain temporal synchronicity has been demonstrated to be correlated with preference of audiovisual products (Dmochowski et al., 2014), although it is not clear if the effect is distributed or localized in certain brain areas. Moreover, it is also not clear whether this measure offers additional predictive value in addition to the more commonly used measure of activation intensity (Knutson & Genevsky, 2018).

1.4 Neural representations of consumer experience

In this dissertation, I intend to explore and analyze neural representations of consumer experience. By neural representation, I refer to the multi-voxel BOLD signal patterns during a consumer experience, recorded either at a single time point or over a period of time.

The motivation of representation-based analysis is to explore the following questions:

Can we use neural representations to gain access to nonverbal experience of consumers? Neural representations contain multidimensional information based on which one can theoretically infer mental content, as multiple neuroscientific studies have demonstrated (Horikawa, Tamaki, Miyawaki, &

Kamitani, 2013; Ishai et al., 1999; Miyawaki et al., 2008; Nishimoto et al., 2011). In Chapter 2, I will look into how neuroimaging can be used to ‘decode’ consumer knowledge, specifically the visual image consumers associate with a brand. 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, individual neural profiles of brand image can be generated. These neural profiles track the participant’s own self-report brand perception, and in aggregate offer a measure of brand image strength. Overall, the study will demonstrate the potential of analyzing representational similarity of neuroimaging data to study multi-sensory, nonverbal consumer knowledge and experience.

Can we use neural representations to gain access to ephemeral experience of consumers? As noted above, real-time tracking of emotional responses of consumers is difficult with traditional self-report methods; direct brain measurements open up an information stream that can be tapped into. Since emotions are known to be encoded by a constellation of brain networks (Kragel & LaBar, 2015; Saarimäki et al., 2016), MVPA should be a prime tool to tackle such dynamic experiences. In Chapter 3, I will explore the feasibility of using neural representations from brief, stable affective episodes (viewing affective pictures) to decode extended, dynamic affective sequences in a naturalistic experience (watching movie-trailers). Using this approach, we found that decoded valence and arousal responses during video watching tracked self-reported valence and arousal; in addition, the decoded affect time series could be used to identify movie-trailers, suggesting they represented the common experience across participants. This study provides further support for the possibility of using pre-trained neural representations to decode dynamic affective responses of an independent sample during a naturalistic experience.

Can we use neural representations to further improve behavioral predictions? Building on existing literature of ‘neuroforecasting’ (Knutson & Genevsky, 2018), which base behavioral prediction on activation of specific brain sites,

in Chapter 4, I intend to investigate if representation-based analysis offers additional information on market outcome prediction. Specifically, I draw inspiration from the latest advancements in inter-subject correlation research (i.e., the consistency of neural responses across individuals; Nastase et al., 2019). I will attempt to identify the neural substrates where inter-subject similarity in responses to videos predicts out-of-sample preference. Findings of this study show that spatiotemporal neural similarity at temporal lobe and cerebellum predict out-of-sample preference and recall. Moreover, neural similarity provided unique information on out-of-sample preference above and beyond in-sample preference. Overall, this study suggests that neural similarity at temporal lobe and cerebellum – traditionally associated with sensory integration and emotional processing – may reflect the level of engagement with video stimuli.

In the last chapter, I will summarize the findings of the three chapters and discuss the implications for marketing practice. My findings will also lead to a more informed discussion of the future research directions in consumer neuroscience, as well as illuminate on the limitations and potential pitfalls of this novel approach.

1.5 Declaration of contribution

In this section, I state my contribution to the empirical chapters (Chapters 2-4) of this dissertation and also acknowledge the contribution of other parties involved.

For Chapter 2, the author of the dissertation (HYC), the promoter (AS) and the daily supervisor (MASB) jointly formulated the research question. HYC conducted literature review, designed the experiment and executed the data collection with the assistance of Jennifer van den Berg. HYC conducted the data analysis, interpreted the findings and wrote the manuscript with the input from AS and MASB. The three authors have edited and approved the

final manuscript. This chapter has been published in the August 2018 issue of *Journal of Marketing Research* (Chan, Boksem, & Smidts, 2018).

For Chapter 3, MASB, AS, Vincent C. Schoots (VCS), and Alan G. Sanfey (AGS) designed the experiment. VCS executed the data collection. HYC, VCS, AS, AGS and MASB formulated the research question, HYC conducted the data analysis, interpreted the findings and wrote the manuscript with the input from AS and MASB. HYC, MASB, and AS have edited the final version of the manuscript, which all authors approved. This chapter has been published in *NeuroImage* (Chan, Smidts, Schoots, Sanfey & Boksem, in press).

For Chapter 4, Roeland C. Dietvorst (RCD), MASB and AS designed the experiment and RCD collected the data for Study 1a and 1b. VCS, AS, and MASB designed the experiment and VCS collected the data for Study 2. HYC formulated the research question, conducted the data analysis, interpreted the findings, and wrote the manuscript with the input from AS and MASB. HYC, MASB, and AS have edited the final version of the manuscript, which all authors approved. This chapter has been published in the August 2019 issue of *NeuroImage* (Chan, Smidts, Schoots, Dietvorst, & Boksem, 2019).

Chapter 2

Neural profiling of brands¹

2.1 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.

¹ Part of this chapter has been published (Chan et al., 2018); for supplementary materials in this chapter, please refer to <https://doi.org/10.1509/jmr.17.0019>

2.2 Introduction

Communicating a brand's image clearly and effectively to consumers is crucial for building brand equity (Keller, 1993, 2001; Park, Jaworski, & MacInnis, 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 (D. A. Aaker, 1991; Brakus et al., 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 & Hutchinson, 1987; Zaltman & 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 chapter 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.

2.2.1 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 et al., 2009; Fournier, 1998; John et al., 2006; Krishnan, 1996; Low & Lamb, 2000; Roth, 1994). One of the most commonly used self-report instruments is the brand personality questionnaire (J. 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 & Gutman, 1988), and the Zaltman Metaphor Elicitation Technique (Coulter & 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 &

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 et al., 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 et al., 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 & 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?

2.2.2 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 chapter, 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 2.1 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 & Burns, 1997; Henderson, Cote, Leong, & Schmitt, 2003; Kirmani & Zeithaml, 1993; LaBarbera, Weingard, & 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 (W. Chen et al., 1998; Kosslyn, Ganis, & Thompson, 2001; Kosslyn & Thompson, 2003; Roland & Gulyas, 1994). Furthermore, neural representations evoked in visual perception and in visual imagery appear to share common features (Cichy, Heinze, & Haynes, 2012; O'Craven & Kanwisher, 2000; Slotnick, Thompson, & 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.

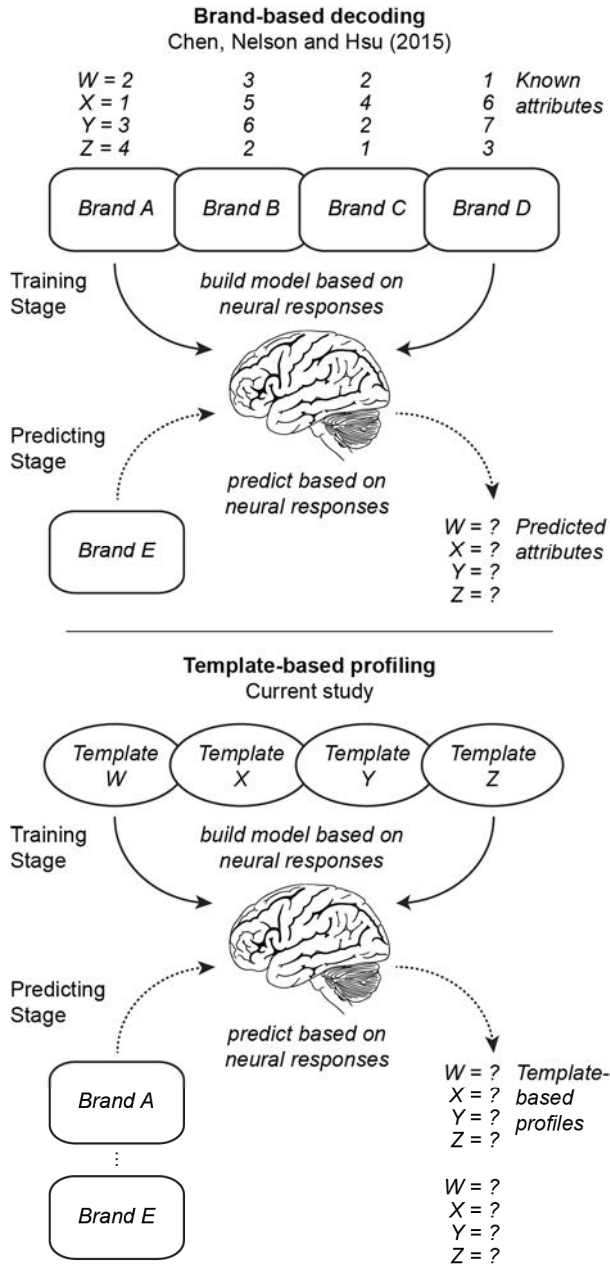


Figure 2.1 Overview of brand-based decoding and template-based profiling approaches

2.3 Study 1: Building individual neural profiles

2.3.1 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.

2.3.1.1 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, & 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

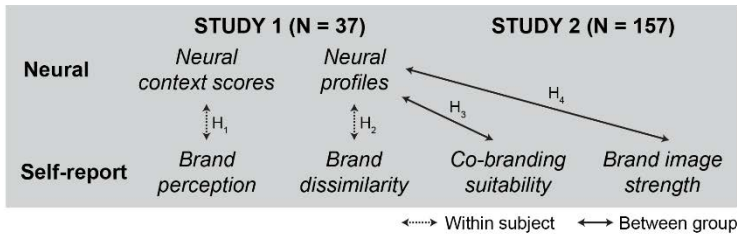
sociological literature: kin versus non-kin, sexual-romantic versus non-sexual-romantic, cohabiting versus noncohabiting, hierarchical versus egalitarian (Blumstein & Kollock, 1988). It is important to note that our choice of the social context images was not an attempt to comprehensively describe all 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).

2.3.1.2 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 2.2 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:

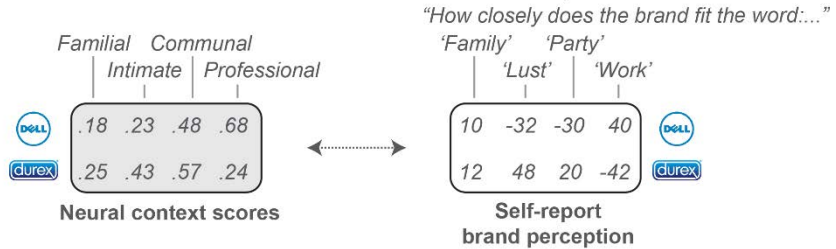
H₁: Brand-imagery neural patterns correspond with the individual's self-report perception of the brand's image.

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.

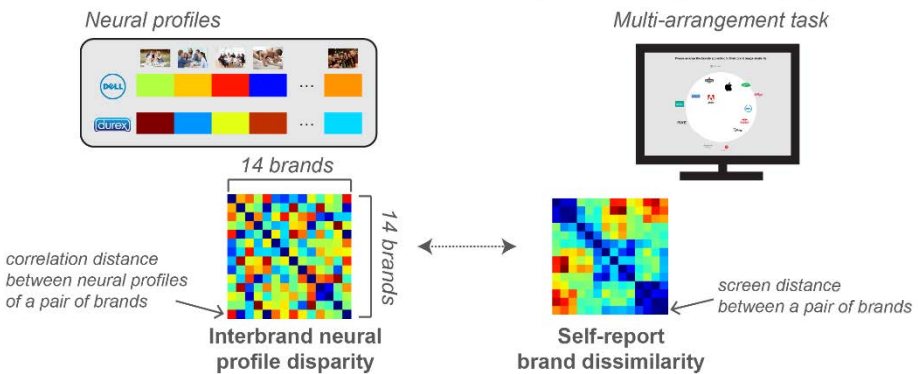


STUDY 1: Within each participant,

do neural context scores correlate with self-report brand perception? (H_1)



does interbrand neural profile disparity correlate with self-report brand image similarity? (H_2)



STUDY 2: In aggregate,

does group-averaged interbrand neural profile disparity predict co-branding suitability? (H_3)

does intersubject neural profile disparity predict brand association strength? (H_4)

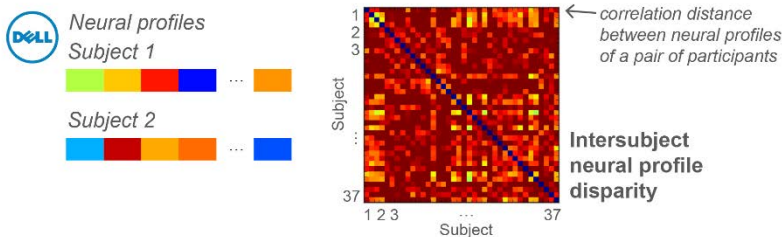


Figure 2.2 Overview of the hypotheses

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:

H₂: Brands that elicit similar neural profiles within an individual are perceived to be similar by that individual.

2.3.2 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.

2.3.2.1 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).

2.3.2.2 Scanner tasks

There were two tasks that took place inside the scanner, separated by the acquisition of the structural (anatomical) scan (Figure 2.3A). 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).

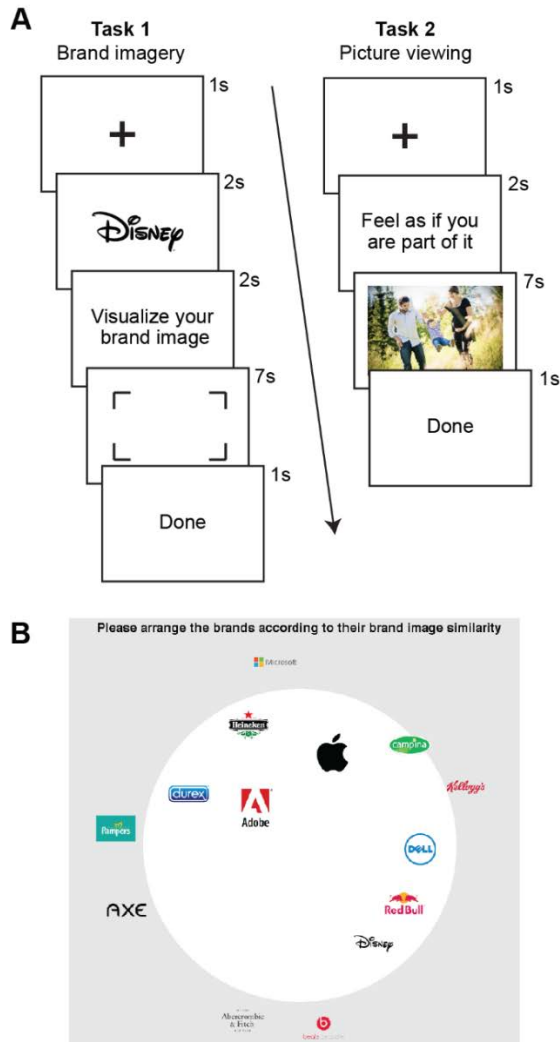


Figure 2.3 Procedure of scanning task (A) and screenshot of multiple arrangement task (B)

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.

2.3.2.3 Brand similarity

Immediately after scanning, participants evaluated similarities between brands in terms of brand image. This was done by the multi-arrangement task (Kriegeskorte & 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 2.3B 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).

2.3.2.4 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.

2.3.3 Neuroimaging data analysis

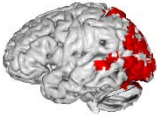
The neuroimaging data were first preprocessed detailed in the web appendix. The overall approach of the analysis is as follows (see Figure 2.4 for an overview):

2.3.3.1 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

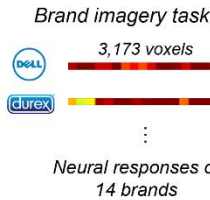
selected top 1% voxels in each direction (i.e., voxels with contrast values below the 1st percentile or above the 99th percentile), and then the selected voxels from all six group-level contrasts were superimposed to form our region of interest (ROI) mask for data extraction for all participants. (Varying the threshold to 0.5% or 2.5% did not materially affect the results; see S.A. 3.)

1. Voxel selection

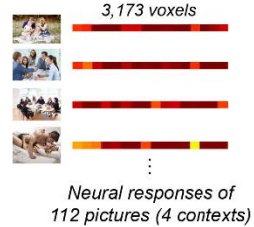


Voxels selected by 6 pairwise contrasts of picture categories

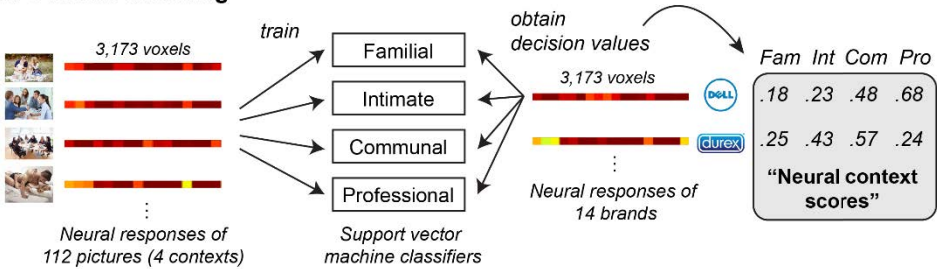
2. Data extraction



Picture viewing task



3. Content decoding



4. Profile compiling

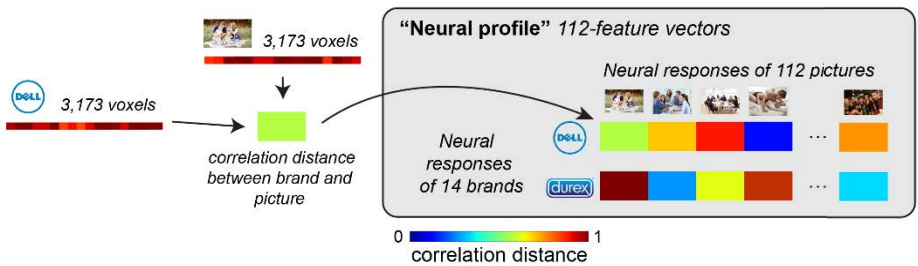


Figure 2.4 Schematic diagram of the analysis

2.3.3.2 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 \times 6 repetitions) were obtained.

2.3.3.3 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 \times 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.

2.3.3.4 Profile compiling

Separately, within participant, we calculated the correlation distances between the 84 extracted volumes (14 brands \times 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 inter-subject disparity matrix within each brand, which describes how neural profiles among participants are similar or different within a given brand.

2.3.4 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 2.5).

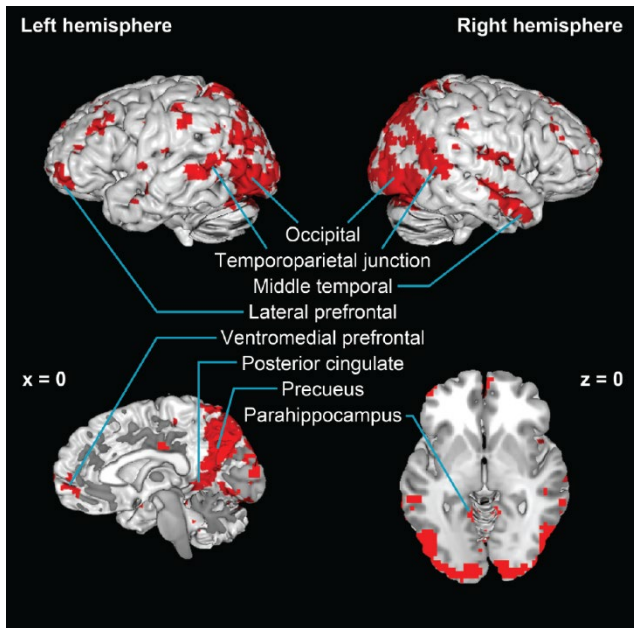


Figure 2.5 Voxels selected from six contrasts using 1% threshold in each direction, covering several areas associated with episodic memory, self-awareness and the default network

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, Caddigan, Li, & Beck, 2009), or emotional valence of speech (30% with chance level at 20%, Ethofer, Van De Ville, Scherer, & Vuilleumier, 2009). Having established that our classifiers are able to distinguish between the different social contexts, we then proceeded to test our hypotheses.

2.3.5 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 2.6, 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 2.6, 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 2.1). 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; $ps < .05$), 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.

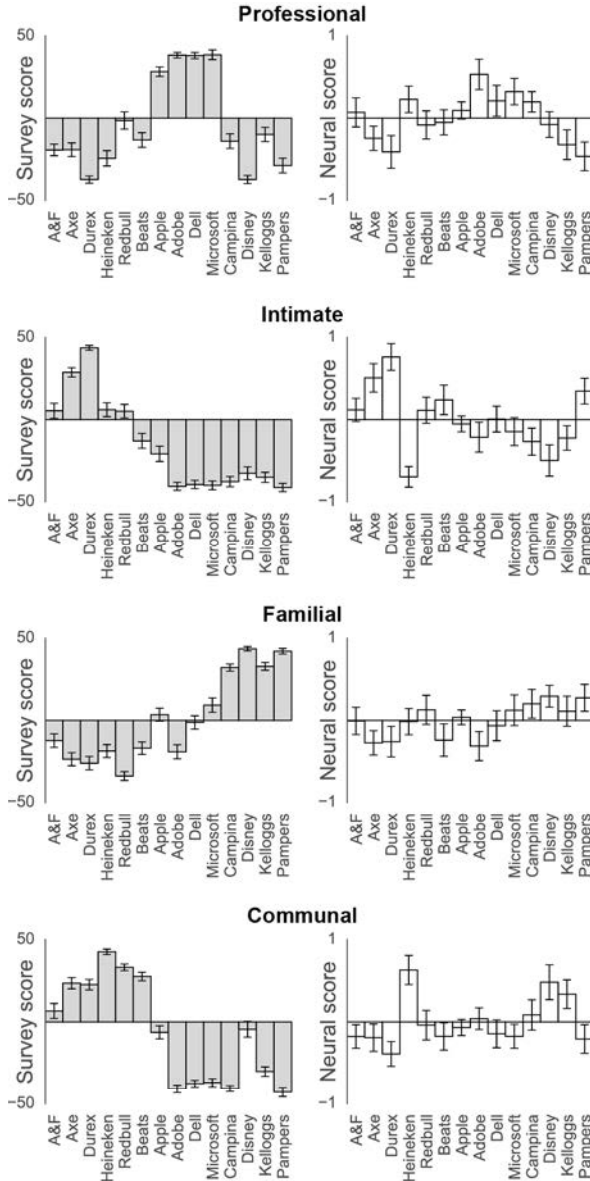


Figure 2.6 Self-report brand perceptions and standardized neural context scores

Table 2.1 Linear mixed-effects models (participants as random intercepts) of self-report brand perceptions with standardized neural context scores²

<i>Model</i>	1	2	3	4	5
	Professional	Intimate	Familial	Communal	Together
<i>Neural context score</i>					
<i>F statistics of fixed effects</i>					
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
<i>Coefficient for each context</i>					
Professional	.185				.194
Intimate		.141			.104
Familial			.206		.196
Communal				.061	.062

2.3.6 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 (Kriegeskorte, Mur, & 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. We then 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.

² In models 1-4, context scores were modelled separately; they were modelled together in model 5. Marginal R² is a measure of variance explained by fixed factors.

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 2.7. 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.

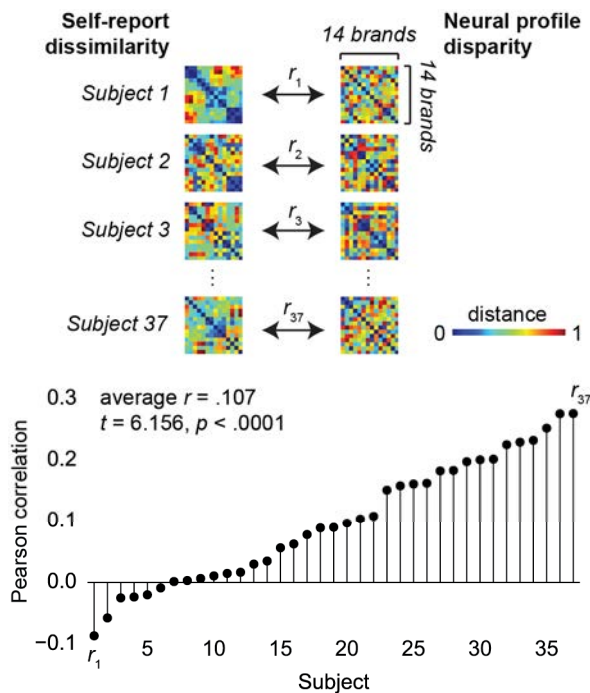


Figure 2.7 Individual correlations between self-report brand image dissimilarity and interbrand neural profile disparity

2.4 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 2.2 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 & 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, & 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, & Leeflang, 2008; Simonin & Ruth, 1998; van der Lans, Van den Bergh, & Dieleman, 2014). Here we posit that brands with similar neural profiles will be judged by consumers as suitable co-branding partners. We therefore propose that:

H₃: 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:

H₄: Brands that elicit more similar neural profiles across individuals are perceived to have a stronger brand image.

2.4.1 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:

2.4.1.1 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.

2.4.1.2 Brand image strength

In addition, they also completed the consumer-based brand equity scale (Yoo & 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.

2.4.2 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 2.2).

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 2.8, $r = -.384$, $p < .0001$). 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.

2.4.3 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 inter-subject 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).

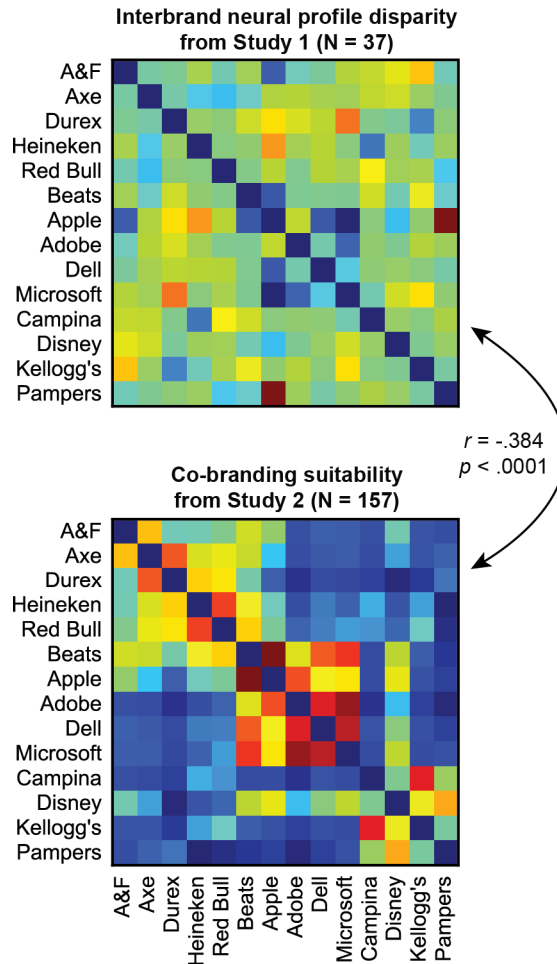


Figure 2.8 Co-branding suitability from Study 2 participants and aggregated interbrand neural profile disparity from Study 1 participants

Brand attitude did not significantly correlate with average inter-subject neural profile disparity ($r = -.329$, $p = .255$ based on 10,000 random permutations of brands in calculating the inter-subject 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 inter-subject neural profile disparity and brand image

strength was significant (Figure 2.9, $r = -.627$, $p = .013$ 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.

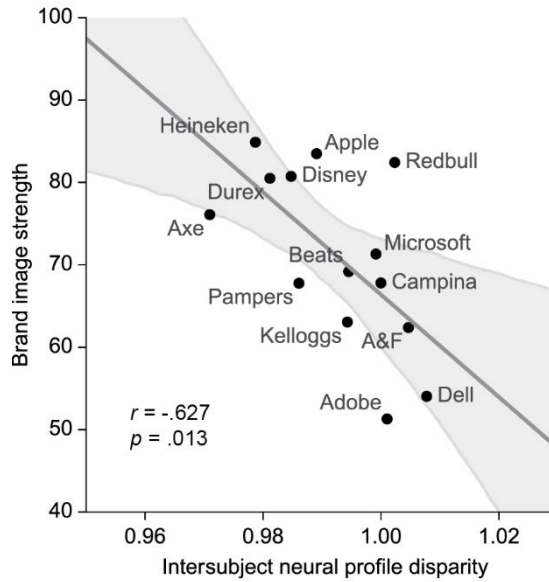


Figure 2.9 Inter-subject neural brand profile disparity, brand image strength and brand attitude.³

2.5 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 (D. A. 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 (D. A.

³ P-value was calculated by Monte Carlo sampling of neural profiles (10,000 permutations).

Aaker & Biel, 2013; Dahlen, Lange, & Smith, 2010; Faircloth, Capella, & 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 chapter, 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.

2.5.1 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, & 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 & Trott, 2007; Yakimova & Beverland, 2005), studies showed that brand image changes due to spillover effects during co-branding or brand alliance programs (Washburn, Till, & 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 & 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 et al., 2006; Simonin & Ruth, 1998; Thompson & Strutton,

2012) 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 & Andrews, 1995), the use of neuroimaging methods promises a new way to capture and quantify perceptual fit between brands.

2.5.2 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 inter-subject consistency in neural responses (Hasson, Malach, & Heeger, 2010). Neuroimaging studies have shown that neural activities are often synchronized across individuals who process narratively rich stimuli, such as spoken stories (Silbert, Honey, Simony, Poeppel, & Hasson, 2014), speeches (Schmälzle, Häcker, Honey, & Hasson, 2015), movies (Hasson et al., 2010), and video clips (Nummenmaa et al., 2012). Moreover, the extent to which inter-subject consistency occurs – commonly referred to as neural reliability – seems to be a measure of consumer engagement, in terms of viewership and ticket sales (Barnett & 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 & Canli, 2004)? Further research is required to answer these questions.

2.5.3 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 inter-subject 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).

2.5.4 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, & 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, & 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, Peeters, van Hecke, & Sunaert, 2007), touch (Gallace & 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.

Chapter 3

Decoding affective responses to videos⁴

3.1 Abstract

This study explored the feasibility of using neural representations from brief, stable affective episodes (viewing affective pictures) to decode extended, dynamic affective sequences in a naturalistic experience (watching movie-trailers). Twenty-eight participants viewed pictures from the International Affective Picture System (IAPS) and, in a separate session, watched various movie-trailers. After feature selection and hyperalignment, we trained support vector machine classifiers on neural responses elicited by affective pictures across participants. We then used the common response classifiers to decode affective states of a new participant both during picture viewing and during movie-trailer watching. We found that decoded valence and arousal responses corresponded to picture categories, and tracked self-reported valence and arousal during video watching. In addition, the decoded affect time series could be used to identify movie-trailers, suggesting they represented the common experience across participants, and that this experience was unique for every video. Our findings provide further support for the possibility of using pre-trained neural representations to decode dynamic affective responses of an independent sample during a naturalistic experience.

⁴ A version of this chapter has been published (Chan et al, in press). For supplementary materials in this chapter, please refer to <https://doi.org/10.25397/eur.8297843>

3.2 Introduction

In recent years, numerous studies have attempted to use signals recorded from the brain to infer emotional states (Chikazoe, Lee, Kriegeskorte, & Anderson, 2014; Kassam, Markey, Cherkassky, Loewenstein, & Just, 2013; Kim et al., 2015; Klasen, Kenworthy, Mathiak, Kircher, & Mathiak, 2011; Kragel & LaBar, 2015; Peelen, Atkinson, & Vuilleumier, 2010; Saarimäki et al., 2018, 2016). Using either a circumplex model (Russell, 1980) or discrete emotion classes (Panksepp, 1982), these functional magnetic resonance imaging (fMRI) studies have uncovered neural representations, in the form of spatial patterns of blood oxygenation level dependent (BOLD) signals, that are associated with certain emotional experiences. What distinguishes these more recent studies from the preceding decade of research on neural processing of emotions (Kober et al., 2008) is two-fold. First, the increasing popularity of multi-voxel pattern analysis (Kragel, Koban, Barrett, & Wager, 2018; Norman et al., 2006) has led to the extraction of information over a distributed brain network instead of examining isolated voxels; second, rather than locating neural substrates associated with different emotions, there is a shift in focus towards making predictions of emotional responses based on distributed neural patterns.

In experimental studies, emotions are often evoked by various external means such as video, music, or pictures. An important question would be whether any neural representations associated with these affective stimuli are specific within or common across modalities. Furthermore, another line of inquiry is whether different individuals exhibit the same affective neural patterns. To both ends, there is evidence suggesting that neural representations, at least to some extent, are modality-general and individual-invariant. For example, common affective neural patterns have been found between words and pictures (Kassam et al., 2013), movies and imagery (Saarimäki et al., 2016), faces and situations (Skerry & Saxe, 2014). Chikazoe and colleagues (2014) found that different participants shared neural patterns of valence evoked by

image and taste, while Kragel and LaBar (2015) observed across participants distinct neural patterns for various emotions evoked by either music or movies.

In most of these studies, emotions evoked by pre-selected stimuli (e.g., a video clip that triggers disgust, a picture of a cute puppy meant to induce happiness) were studied as a collection of isolated, distinct mental states. Verifying the validity of neural representations of emotions was mainly by cross-validating brain responses during these brief affective episodes (either within or across participants and modalities). However, given that emotions are essentially momentary experiences, surprisingly few studies examined the temporal changes of affect in an extended period of emotionally varying experience. For example, Nummenmaa and colleagues (2012) investigated how neural synchronization tracked moment-by-moment changes in valence and arousal while watching movie clips. More recently, Eijlers and colleagues (2019) used affective neural patterns derived from electroencephalography (EEG) to examine the temporal change of emotions during movie watching.

The aim of the present study is to test whether affective neural representations, based on brief and isolated episodes of emotions, could be used to decode a time-variable emotional experience (here, watching movie-trailers). That is, can episode-based affective neural patterns be used to interpret fleeting moments of emotions under more naturalistic conditions? We attempted to extract affective neural representations evoked by picture viewings, then use these representations to infer moment-by-moment emotional states while participants watched movie-trailers. While it is difficult to obtain the ground truth for such transitory affective changes, we planned to examine the validity of such approach in two ways: First, we tested whether the inferred affective time series during the extended experience track the retrospective summary ratings of valence and arousal by the participants. Second, we tested whether these time series could serve as an emotional fingerprint of naturalistic stimuli; that is, could we identify movie-trailers across participants based on the time series of affective neural

responses? This would suggest that, while the intensity of the emotional experience may differ across participants, the temporal sequence of these experiences is consistent across viewers, and unique for every video, tracking the dynamics of the experience evoked by that video.

3.3 Materials and Methods

3.3.1 Participants

We recruited 31 healthy Dutch volunteers via the recruitment system of a university. One participant had to be excluded due to falling asleep, and two more due to excessive head movements. These are omitted from all behavioral and neural analyses. The final sample thus consisted of 28 participants (14 women, age 18–27, mean age 20.9). The study was approved by the local ethics committee, in line with the Declaration of Helsinki. All participants signed informed consent prior to participation.

3.3.2 Materials and procedures

Participants received a fixed fee of €10 per hour. After signing informed consent, participants were taken to the MRI scanner, and performed a number of tasks in separate scanning sessions. The two tasks presented in this report were movie-trailer watching and picture viewing.

3.3.2.1 Movie-trailer watching

Participants viewed 18 unedited movie trailers (see Table 3.1), chosen with the aim to represent a wide range of genres and commercial successfulness (as measured by box office returns) while avoiding extreme content (e.g., horror) (see supplementary material S1 for more details on movie selection).

Participants were screened prior to inclusion to ensure that they had not seen any of our selected movies already. The 18 movie trailers were presented to

the participants in random order. (One participant did not watch the movie trailer M16 due to technical error.) Presentation of the trailers was preceded and followed by a picture of the cover (3s) of the DVD to make clear which movie the trailer belonged to. Immediately following each movie-trailer, participants were asked to state (1) their expected liking of the movie on a five-star-scale (zero stars possible with half-star increments); (2) willingness to pay (WTP) to obtain a DVD of the movie (€0 - €2.5, with 25 cents increments) under a Becker-DeGroot-Marschak (BDM) auction procedure (Becker, Degroot, & Marschak, 1964); (3) valence with the self-assessment manikin (SAM), a nine-point visual analog scale (Hodes, Cook, & Lang, 1985); and (4) arousal with SAM. All of the ratings were self-paced without time limit. We focused on the self-report valence and arousal scores for this analysis.

Before and after all movie-trailers were shown, we showed emotionally neutral movie excerpts (scenes from *Comment j'ai tué mon père* [2001], each 90s in length) for participants to return to baseline emotional state. In addition, after the fourth and the twelfth trailer, we showed a scrambled version of trailer of either M5 or M13 (order counterbalanced across participants) with the original soundtrack replaced by white noise of same dynamic amplitude. These were not used in the analysis.

Table 3.1 Movie trailers used in the study (movie information from the International Movie Database)

Title	Code	Year released	Genre ⁵	Length (s)
<i>The Namesake</i>	M1	2006	D	150
<i>Pollock</i>	M2	2000	B,D	141
<i>The Town</i>	M3	2010	C,D,T	145
<i>Quills</i>	M4	2000	B,D	143
<i>Love & Basketball</i>	M5	2000	D,R,Sp	142

⁵ Genre legend: A = action; B = biography; C = crime; D = drama; F = fantasy; Mu = musical; My = mystery; R = romance; Sf = sci-fi; Sp = sport; T = thriller; W = western

Title	Code	Year released	Genre ⁵	Length (s)
<i>Takers</i>	M6	2010	A,C,D	141
<i>Northfork</i>	M7	2000	D,F	143
<i>Waist Deep</i>	M8	2006	A,C,D	133
<i>Michael Clayton</i>	M9	2007	C,D,M	134
<i>The Debt</i>	M10	2010	D,T	142
<i>Idlewild</i>	M11	2006	C,D,M	130
<i>To Save a Life</i>	M12	2009	D	137
<i>Confidence</i>	M13	2003	C,T	125
<i>Extraordinary Measures</i>	M14	2010	D	147
<i>Impostor</i>	M15	2001	D,Sf,T	66
<i>Harsh Times</i>	M16	2005	A,C,D	131
<i>The Warrior's Way</i>	M17	2010	A,F,W	136
<i>Gracie</i>	M18	2007	B,D,Sp	131

3.3.2.2 Picture viewing

Before movie-trailer watching, in a separate session, we showed 156 pictures, each for 2s successively, drawn from the International Affective Picture System (IAPS) database (Lang et al., 2008). They belong to six categories varying in the valence-by-arousal space: (1) positive valence/high arousal; (2) positive valence/low arousal; (3) negative valence/high arousal; (4) negative valence/low arousal; (5) neutral valence/medium arousal; and (6) neutral valence/low arousal. They were matched for content of bodies, faces, animals and plants (see supplementary material S2 for more description of the pictures). Pictures from each of the first five categories were shown in two 12-picture (24s) blocks (i.e., 5 blocks \times 2 runs), presented in random order within each run. In between blocks, a 4-picture (8s) block from the last category (neutral valence/low arousal) were shown to allow the emotional response to return to baseline. Of interest for the present study were the first four picture categories.

3.3.3 FMRI acquisition and preprocessing

Subjects were scanned using a Siemens (Erlangen, Germany) Skyra 3 Tesla MRI scanner, with a 32-channel head coil. Subjects could respond using a right-hand 4-button response device. A mirror mounted on the head coil ensured that participants could view the projector screen mounted at the back of the scanner. Functional data was acquired with a T2*-sensitized parallel imaging multi-echo sequence, with echo times (TE) at 9, 19.3, 30 and 40 ms. Thirty-four horizontal slices were acquired in ascending order (3.0 mm slice thickness, 0.5 mm slice gap, 3.5×3.5 mm in-plane resolution, 64×64 voxels per slice, flip angle 90° , total repetition time (TR) 2.07 s). The first 30 volumes (before the start of each session's task) were used for echo-weighting. Prior to preprocessing, the four read-outs acquired via the multi-echo sequence were combined and realigned by using standard procedures described by Poser et al (2006). A T1-weighted image was acquired for anatomical reference ($1.0 \times 1.0 \times 1.0$ mm resolution, 192 sagittal slices, TE 3.03 ms, TR 2300 ms).

Data pre-processing 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 echo of the first volume. Images were then corrected for differences in slice acquisition time. The anatomical image was co-registered with the mean functional image for each participant. Functional and anatomic images were then normalised to Montreal Neurological Institute (MNI) space. Finally, the normalised functional images were smoothed using a 3mm full-width-at-half-maximum (FWHM) Gaussian kernel. Linear detrending, regressing out white matter and background signal, and voxel- and session-wise z-scoring were performed before analysis. A time shift of 6s was also added throughout the analysis to account for hemodynamic response delay. Multivariate pattern analysis was carried out in Python 2.7 with the PyMVPA toolbox (Hanke et al., 2009).

3.3.4 FMRI data analysis

3.3.4.1 Selecting voxels responsive to affective picture categories

We first located voxels responsive to affective picture categories, i.e., those which showed differential activations between positive and negative valence pictures, and between high and low arousal pictures. This was done by univariate analysis with general linear models defined for each subject using a box-car function to model the picture blocks. Two regressors of non-interest, average white matter signal and average background signal, were entered together with a constant. The first level maps were then entered into a random effects second-level analysis.

3.3.4.2 Inter-subject hyperalignment

Since we aimed to uncover shared neural representations of affective states across individuals, before doing so we considered ways to optimize brain alignment across individuals. To this end, we used functional response tuning as an extra step in addition to anatomical alignment (Haxby, Connolly, & Guntupalli, 2014). Based on this particular approach called ‘hyperalignment’ (Haxby et al., 2011), individual subjects’ voxel spaces were transformed into a common model space by comparing inter-subject neural responses to identical stimuli. For each subject, spatio-temporal responses to common stimuli (i.e., during movie-trailer watching) were treated as a single n -dimensional vector with t time points (where n is the number of voxels to be analysed). Using Procrustean transformation, these vectors can be rotated to obtain optimal alignment (i.e. smallest Euclidean distances) among subjects. The procedure created, for each subject, a transformation matrix which could be applied on the corresponding voxel space. The transformation from individual voxel space to a common space has been shown to improve between-subject classification accuracy (Haxby et al., 2011).

Specifically, each participant's scan volumes of the 18 movie trailers (35 minutes 47 seconds in total) were re-sliced in the same order, resulting in a 1168-volume vector. (For the participant who did not watch the movie trailer M16 due to technical error, mean responses of that 63 volumes from other participants were used instead.) Transformation matrices were estimated separately for each contiguous cluster, after which hyperalignment was applied to both picture viewing and movie-trailer watching data such that all participants' voxel responses were transformed to a common space.

3.3.4.3 Training and testing shared-response valence and arousal classifiers

Two linear support vector machine (SVM) classifiers (one for valence and one for arousal) were trained on the picture viewing data. A leave-one-subject-out approach was used here, such that training data came from all-but-one participants. Then, the trained classifiers were used to decode the valence (positive or negative) and arousal (high or low) states of the remaining participant during picture viewing and movie-trailer watching. We decoded the movie-trailer data volume-by-volume, yielding for each trailer a time series of binary valence and binary arousal scores.

For picture viewing, statistical significance of classification accuracy was evaluated based on the binomial distribution. For movie-trailer watching, the neural valence / arousal scores of a movie-trailer were calculated as the proportion of volumes within the video presentation classified as having positive valence / high arousal. Mixed effect regression models were then used to examine the statistical relationship between self-report valence / arousal scores and neural scores.

3.3.4.4 Examining valence and arousal time series of movie-trailers

If the valence and arousal classifiers extract meaningful moment-by-moment changes in affective responses to movie-trailers, it follows that the resultant

time series should contain information specific to each of the movie-trailers. That is, if the classifiers – trained on out-of-sample neural responses to affective pictures – reliably differentiate the dynamics of emotional states during an experience shared among participants, the time series should contain similar temporal patterns across participants, but should be unique to each video. To verify this, we performed a leave-one-subject-out classification of movie-trailers based on the valence and arousal time series obtained from the remaining participants.

3.3.5 Code accessibility and data availability

The data that support the findings of this study, including preprocessing and analysis scripts, are available in an open repository ⁶.

3.4 Results

3.4.1 Behavioral responses to movie-trailers

The 18 movie-trailers evoked a range of valence and arousal responses, based on participants' self-report ratings (group-average valence [1-9, negative to positive] for movie-trailers: min = 4.60, median = 5.27, max = 6.35; group-average arousal [1-9, low to high]: min = 2.79, median = 4.77, max = 6.18; see supplementary material S3 for detailed descriptive statistics). Self-report valence and arousal scores were weakly correlated ($r = .166$, $p < .001$). Inter-subject arousal rating agreement of movie-trailers, based on average inter-subject correlations, was .305; while inter-subject valence rating agreement was weaker at .073, meaning that participants gave rather idiosyncratic valence ratings to the same set of movie-trailers.

⁶ https://github.com/chanhangyee/affect_decoding

3.4.2 Brain areas responsive to affective picture categories

Bidirectional t -contrasts were created for each subject comparing: (1) positive versus negative valence (collapsing over high and low arousal); (2) positive versus negative valence (high arousal only); (3) positive versus negative valence (low arousal only); and (4) high versus low arousal (collapsing over positive and negative valence). Significant results, defined as $p < .001$ uncorrected and with minimum cluster extent of 20 voxels, were found only in (2) and (4). In both valence and arousal contrasts, we observed significant clusters at the posterior ventral temporal cortex (VTC) (see Figure 3.1A and Table 3.2). We therefore targeted that area by creating a union of the two maps and applying light smoothing (3mm FWHM) in order to obtain a bilateral posterior VTC mask with two contiguous clusters (left: 340 voxels, right: 390 voxels) (Figure 3.1B). Hyperalignment was conducted separately for each of the two clusters. The two corresponding transformation matrices were then applied on each participant's picture viewing and movie-trailer watching data.

Table 3.2 Clusters found in the thresholded maps (cluster size $k > 20$)

Cluster	Cluster size	t_{\max}	x	y	z
Valence	126	5.58	-43	-69	-7
(negative > positive, high arousal)	59	6.18	6	-82	19
	47	4.74	44	-69	-10
Arousal	251	7.67	44	-68	0
(high > low)	219	7.97	-42	-75	1

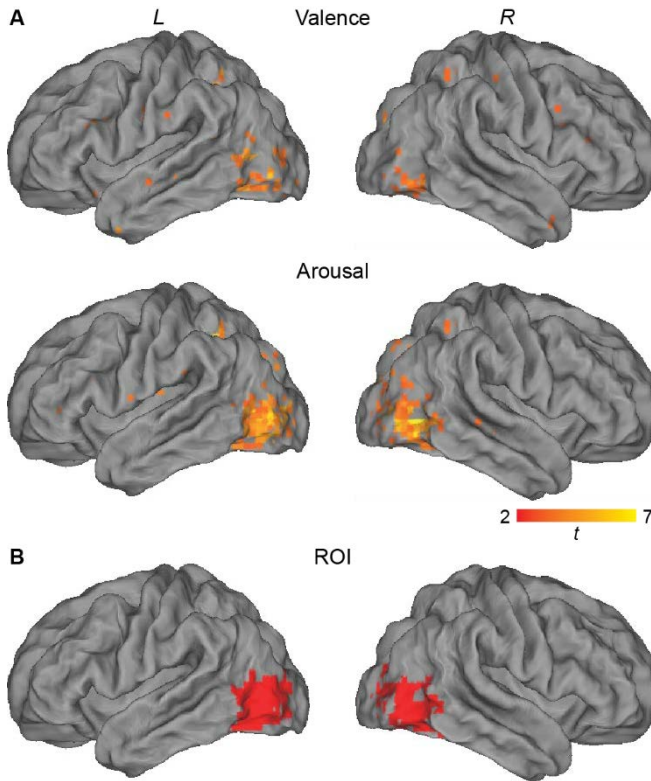


Figure 3.1 Statistical parametric maps thresholded at $p < .001$ uncorrected (A) and region of interest based on the union from the two maps (B)

3.4.3 Decoding picture categories using shared-response classifiers

For each participant, linear SVM classifiers for valence and arousal were trained with picture viewing data pooled over the other 27 participants within the bilateral ROI mask. Neural responses to pictures with high arousal were used to train the valence classifier (1252 volumes from 27 subjects), while the arousal classifier was trained with all pictures (2510 volumes). The classifiers were then applied on the remaining participant's picture viewing data to obtain valence and arousal predictions for each of the volumes under different picture categories. Classification accuracy was defined as the percentage of volumes correctly categorized according to the valence and arousal categories of the pictures.

Wilcoxon signed-rank test showed that hyperalignment boosted performance (valence: $T = 10$, $p < .0001$; arousal: $T = 96$, $p = .015$). After hyperalignment, classification accuracies for valence and arousal significantly exceeded the 50% chance level ($p < .05$) for the majority of participants (median accuracy for valence: 78.5%; arousal: 69.9%; Figure 3.2). Thus, using the ROIs, we could reliably classify neural patterns when individuals viewed pictures of different valence and arousal levels.

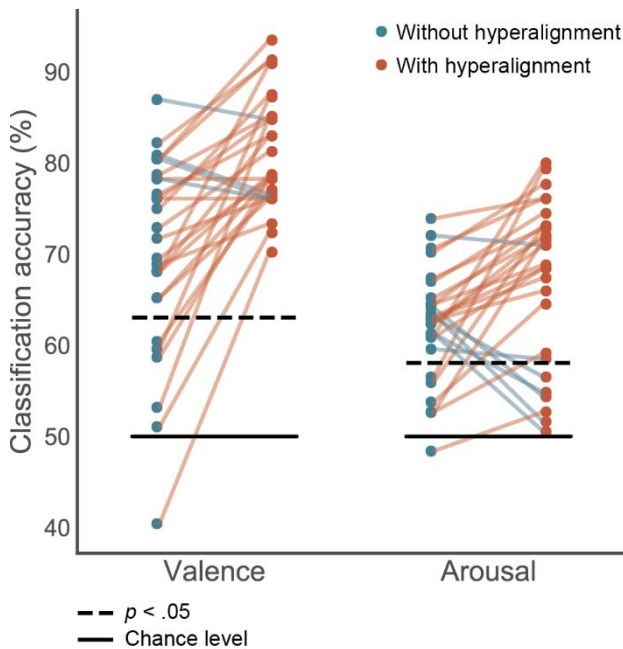


Figure 3.2 Leave-one-subject-out classification accuracy of affective picture categories among participants

3.4.4 Decoding movie-trailers using shared-response classifiers

Neural valence and arousal scores, defined as the proportion of volumes classified as positive valence / high arousal for each movie-trailer, were not correlated ($r = .011$, $p = .805$) showing discriminant validity. Figure 3.3 shows the scatterplot of neural and self-reported valence and arousal scores by movie. The Fisher-transformed mean of within-participant correlations

between neural valence score and self-report valence was .112 (one-sample t test against zero $t = 2.246$, $p = .033$); the mean correlation between neural arousal score and self-report arousal was .156 ($t = 3.761$, $p < .001$). We then examined the association between neural and self-reported valence and arousal scores by using linear mixed-effects models with participant as random intercepts. Neural valence had a significant and positive effect on self-report valence, and neural arousal had a significant and positive effect on self-report arousal (Table 3.3). Importantly, neither neural valence was associated with self-reported arousal, nor neural arousal with self-reported valence. In addition, mean activation of the ROI did not predict self-report arousal and only had a marginal effect on self-report valence. (In supplementary analysis S4, instead of the union mask ROI, we extracted mean activation from voxels based on valence and arousal statistical maps separately, see Figure 3.1A, and found the same result.)

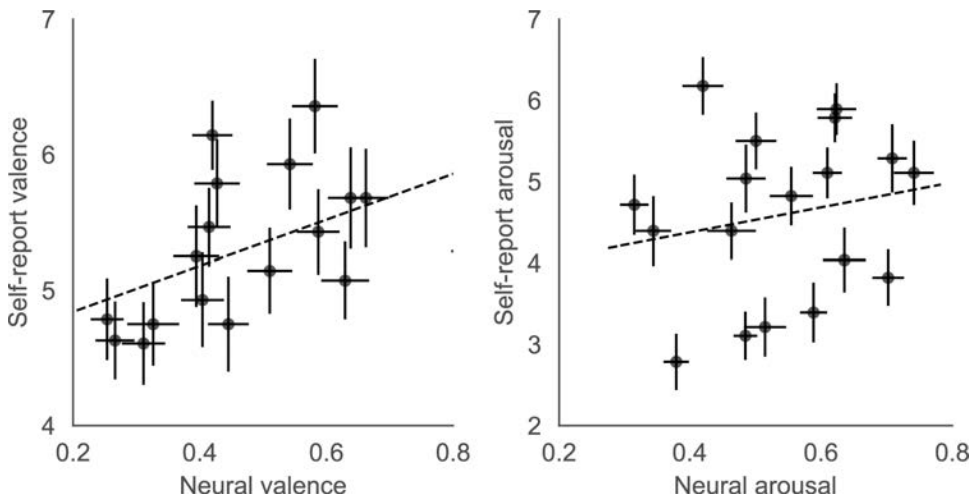


Figure 3.3 Self-report and neural valence and arousal scores grouped by movies.⁷

⁷ Error bars represent standard error

Table 3.3 Mixed effect regression models with participant as random intercepts

	Self-report valence		Self-report arousal	
	coef	<i>p</i>	coef	<i>p</i>
Neural valence score	0.734	.024	-0.319	.389
Neural arousal score	-0.122	.778	1.059	.032
Mean activation at ROI	1.475	.077	0.718	.452

3.4.5 Identification of movie-trailers using classified affect time-series

We further examined whether the time series of the valence and arousal classifications themselves contain movie-trailer-specific information that is common across participants. For this analysis, we used the first 2-minute segment of each movie-trailer time series (60 volumes; the shorter 1-minute-long trailer M15 was excluded). In other words, each movie trailer watched by each participant was represented by a vector of 60 binary features for valence, and 60 for arousal. Leave-one-subject-out cross-validated SVM classification based on valence features yielded a median movie-trailer identification accuracy rate of 70.6%, while classification based on arousal features yielded a median of 76.4%. When using both, the median accuracy was 88.2% (Figure 3.4).

3.4.6 Classified affect time series and narrative content

The results presented above suggest that the decoded time series of affective experience did indeed capture a meaningful temporal pattern as evoked by the trailers. To illustrate how the classified affect time series might track narrative content, we show the time series of two movie-trailers (Figure 3.5), one with most positive valence and one with highest arousal. Visual inspection indeed suggests that peaks and troughs along the neural valence and arousal time series largely tracked the narrative content of the movie-trailers.

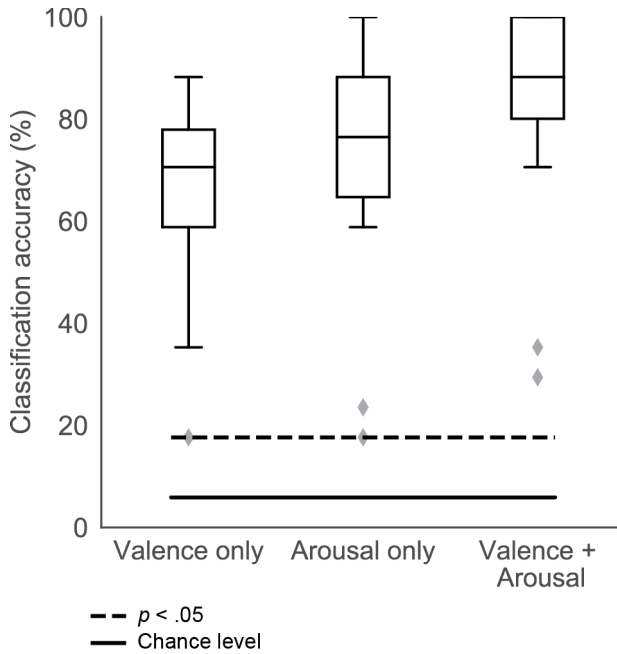


Figure 3.4 Classification accuracy of movie-trailers based on valence and arousal time series

3.5 Discussion

In this study, we first identified brain areas that contained information about emotional valence and arousal, using IAPS pictures. We then showed that neural patterns within these brain areas accurately predicted the affective content of the IAPS pictures. Using the classifiers trained on neural responses to these pictures, we then obtained moment-by-moment valence and arousal time series during movie-trailer watching. We showed that the aggregated time series tracked the participants' self-report ratings of valence and arousal. In addition, we found that the time series also contained movie-trailer-specific affective information, allowing identification of these trailers based on the time series. This suggests that, while the intensity of the emotional experience may differ across participants, the temporal sequence of these

experiences is consistent across viewers, and unique for every video, tracking the dynamics of the experience evoked by that video.

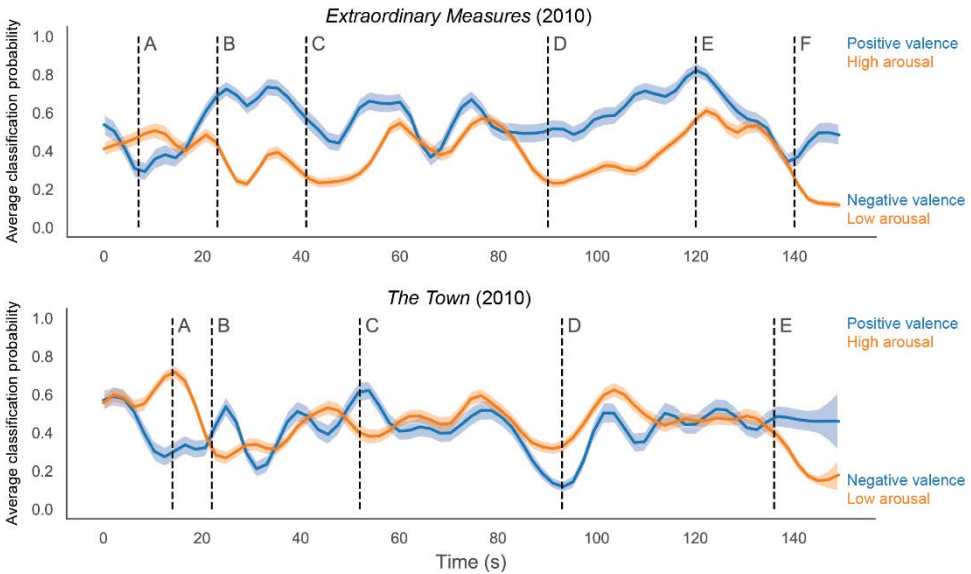


Figure 3.5 Time series of group-averaged valence and arousal classification probabilities of two movie-trailers.⁸

The current findings provide evidence that affective neural patterns extracted from episodic emotional states are similar to those of time-variable, and more naturalistic, emotional experiences. This is important, because it suggests the neural models constructed in a more controlled environment are also applicable in more realistic settings, where emotional states are changing

⁸ Both series were gaussian-smoothed with 1TR sigma along the time axis. Shaded regions represent standard error. Top panel: Notable moments in the trailer of *Extraordinary Measures* (2010): A – Announcement of child’s diagnosis; B – Introduction of the doctor (Harrison Ford) who could potentially save the child’s life; C – Father (Brendan Fraser) expresses frustration; D – Dispute between father and doctor; E – Culmination in the search for the cure; F – Title card and credits. Bottom panel: Notable moments in the trailer of *The Town* (2010): A – Bank robbery and hostage taking; B – Studio vanity card; C – First romantic meeting between male and female leads (Ben Affleck and Rebecca Hall); D – Reveal that the male lead turns out to be kidnapper of the female lead; E – Title card and credits

rapidly. While behavioral studies have been documenting patterns of dynamic changes in emotions (Kuppens & Verduyn, 2017; Nielsen, Knutson, & Carstensen, 2008; Pe & Kuppens, 2012), the way in which these self-reported changes manifest at a neural level has remained unclear. This study represents one of the first steps into bridging the emotion-as-distinct-states and emotion-as-continuous-flow approaches in neuroimaging research.

We found not only that we could decode the emotional categories associated with static affective pictures, but also that the decoded time series of the emotional responses elicited by dynamic stimuli corresponded to the participants' own ratings (in terms of valence and arousal). That is, the more timepoints (here volumes) within the video were classified as positive valence, or high arousal, the higher the participant rated that movie-trailer on valence or arousal, respectively. Moreover, we found that the temporal pattern of the emotional experience within a video was highly consistent across subjects, but unique for every trailer. That is, each video elicited a unique temporal pattern of valence and arousal, and this pattern of the elicited emotional experience was consistent across viewers. This suggests that the decoded time series contains meaningful information not only in the aggregate decoded emotional experience, but also in its dynamics. The plotted time series in Figure 3.5, although merely an illustration, indeed suggests that the decoded dynamic emotional experience appears to track the ups and downs of the narrative of the movie-trailers.

We identified the bilateral posterior VTC as brain areas responsive to affective pictures. Previous studies have found that posterior VTC is responsible for processing valence and arousal, especially with visual stimuli (Colibazzi et al., 2010; Kassam et al., 2013; Klasen et al., 2011; Nielen et al., 2009) but not in other modalities (Chikazoe et al., 2014). Our univariate analysis of affective picture categories did not reveal traditional brain areas associated with emotions, such as the amygdala, thalamus and insula. In additional analyses, we used anatomically defined ROIs at amygdala, thalamus and insula for neural pattern extractions but failed to obtain

significant results. Given the evidence that there exist both modality-general and modality-specific neural coding of affective states (Miskovic & Anderson, 2018), we speculate that the affective neural patterns we extracted in this study were specific to visual stimuli and may not be transferable to other modalities. We also found that hyperalignment increased performance in classification accuracy. This confirms previous results on its use for improving cross-participant classification (Haxby et al., 2011). (In a supplementary analysis, we repeated the procedure without hyperalignment and found that decoded valence and arousal during movie-trailer watching did not track self-report ratings.) However, most of the past applications were limited to visual and auditory processing circuits to uncover a common representational space for sensory percepts (Guntupalli, 2013; Haxby et al., 2011; Nishimoto & Nishida, 2016). More recent studies are expanding towards a whole-brain approach in a search of common space for higher-order processes (Guntupalli et al., 2016). While we applied hyperalignment closer to the original approach by Haxby and colleagues (2011), our findings suggest that this technique is also beneficial to decoding other mental processes such as emotions.

Several limitations of this study should be noted. First, the fact that only neural responses at VTC were used to predict affective content might suggest that the neural representations might be tied to specific low-level visual features instead of affective content. However, a recent study (Bush et al., 2018) compared neural patterns at a broad network of brain areas including VTC that were derived from two independent subsets of IAPS pictures. They found that neural patterns extracted from different picture subsets on separate groups of participants were largely consistent, mitigating the possibility that neural patterns extracted this way represented low-level visual features. Nonetheless, given the fact that we only used posterior VTC here and no other brain networks, further research should focus on establishing whether modality-general representations are capable of tracking dynamic change of specific emotions as well. Second, we only used high-arousal

valence pictures for training the valence classifier, which limits the generalizability of the findings. The reason for using high-arousal pictures only was that we did not find significant valence clusters in our univariate analysis when pictures of low arousal were included. This suggests that our training task, which involved passive viewing of picture blocks, might not be sensitive enough to pick up nuanced changes in the valence dimension of emotion. Third, we did not obtain moment-by-moment self-report measures of valence and arousal (Nummenmaa et al., 2012). Other continuous, unobtrusive measurements such as skin conductance or eye-tracking could also shed more light on the validity of the current findings. Lastly, we adopted a dimensional model of emotions (Russell, 1980) in our study. Previous research have uncovered neural patterns for categorical emotions that are distinct from, and not totally explained by, valence and arousal signals (Kragel & LaBar, 2015). Using categorical emotions for classification may reveal finer-grained affective changes across time that could not be captured by valence and arousal alone, such as co-existence of multiple emotions (Larsen & McGraw, 2011).

In summary, this study explored the feasibility of using neural representations from brief, stable affective episodes (picture viewing) to decode extended, dynamic affective sequences in a naturalistic experience (movie-trailers watching). Our findings demonstrate the potential of using pretrained neural representations to decode affective responses to naturalistic stimuli of an independent sample. Moreover, by extending emotion research from discrete states to dynamic sequences, this study highlights the possibility of augmenting behavioral studies of temporal changes of affect, which rely mostly on self-report measures, with neuroimaging data.

Chapter 4

Neural similarity predicts video preference⁹

4.1 Abstract

The extent to which brains respond similarly to a specific stimulus, across a small group of individuals, has been previously found to predict out-of-sample aggregate preference for that stimulus. However, the location in the brain where neural similarity predicts out-of-sample preference remains unclear. In this study, we attempt to identify the neural substrates in three functional magnetic resonance imaging (fMRI) studies. Two fMRI studies (N = 40 and 20), using previously broadcasted TV commercials, show that spatiotemporal neural similarity at temporal lobe and cerebellum predict out-of-sample preference and recall. A follow-up fMRI study (N = 28) with previously unseen movie-trailers replicated the predictive effect of neural similarity. Moreover, neural similarity provided unique information on out-of-sample preference above and beyond in-sample preference. Overall, the findings suggest that neural similarity at temporal lobe and cerebellum – traditionally associated with sensory integration and emotional processing – may reflect the level of engagement with video stimuli.

⁹ Part of this chapter has been published (Chan et al., 2019); for supplementary materials in this chapter, please refer to <https://doi.org/10.1016/j.neuroimage.2019.04.076>

4.2 Introduction

Recent neuroscientific research, using electroencephalography (EEG) (Barnett & Cerf, 2017; Boksem & Smidts, 2015; Dmochowski et al., 2014) or functional magnetic resonance imaging (fMRI) (Berns & Moore, 2012; Couwenberg et al., 2017; Falk, Berkman, & Lieberman, 2012; Genevsky et al., 2017; Scholz et al., 2017; Venkatraman et al., 2015), has shown the possibility of using neural signals from a small group of individuals to predict the aggregate preference of a separate and larger group of individuals (hereafter population or out-of-sample preference). In most fMRI studies linking brain signals to out-of-sample preference, researchers have focused on signal *intensity*, i.e. the magnitude of blood oxygenation level dependent (BOLD) signal during exposure to the stimulus. Activation at nucleus accumbens (NAcc), medial prefrontal cortex (mPFC), or a combination of both, was found to be predictive of population preference such as, e.g., song downloads, funding success, and advertising elasticities (Knutson & Genevsky, 2018).

A separate body of neuroimaging studies in recent years is concerned with signal *consistency* across individuals' brains. Referred to as either inter-subject correlation (Nummenmaa et al., 2012), similarity (Barnett & Cerf, 2017), synchronization (Hasson, 2004), alignment (Golland, Levit-Binnun, Hendler, & Lerner, 2017), consistency (Lankinen, Saari, Hari, & Koskinen, 2014), or reliability (Dmochowski et al., 2014), researchers found that (a) dynamic natural stimuli (such as videos, narratives, or speeches) evoke similar neural responses across individuals, not only at sensory cortices but also temporal and frontal areas (Hasson et al., 2010); and (b) such neural similarity appeared to be modulated by stimulus quality, such as emotional arousal (Nummenmaa et al., 2012), rhetorical strength (Schmälzle et al., 2015), and humor (Jääskeläinen et al., 2016). Recent EEG studies (Barnett & Cerf, 2017; Christoforou, Papadopoulos, Constantinidou, & Theodorou, 2017; Dmochowski et al., 2014) went further by testing market-level

outcomes and found whole-brain neural similarity predicted online ratings of TV commercials, real-time tweet frequency during TV shows, and box office sales of movies.

Why would neural activation and similarity predict preference not only of the individual, but also of the population? Knutson and Genevsky (2018) posit that neural activation in certain parts of the brain (e.g., NAcc) captures positive arousal to stimuli, a reliably predictive component of choice across different individuals. On the other hand, it is less clear which antecedent of aggregate preference neural similarity might be measuring. Previous studies on neural similarity have shown that synchronized activities across individuals at different brain regions can be induced by various conditions. For example, stronger neural similarity is observed at mPFC and anterior insula when receiving shared emotional information (Golland et al., 2017); superior temporal gyrus (STG) when receiving shared linguistic information (Dikker, Silbert, Hasson, & Zevin, 2014); STG, temporal pole (TP) and parahippocampus when forming episodic memory from shared experience (Hasson, Furman, Clark, Dudai, & Davachi, 2008). Finally, whole-brain similarity, measured by EEG, is higher when individuals pay attention to the same content (Ki, Kelly, & Parra, 2016) and when the content is less complex (Barnett & Cerf, 2017).

An outstanding question is whether the predictive power of neural similarity on out-of-sample preference is concentrated in particular areas, or distributed all over the brain. Areas typically found to display synchronized activities during video watching (Hasson et al., 2010) involve sensory processing (visual and auditory cortices), comprehension (temporal and parietal cortices), and valuation (prefrontal cortex). However, at which stage (or stages) in mental processing, from perception to integration to evaluation, a relationship between neural similarity and aggregate preference can be observed remains elusive.

In addition, recent studies have shown that neural and self-report information may each contain non-redundant signals predictive of out-of-sample preference, such that neural activation improves market-outcome prediction over using self-report measures alone (Berns & Moore, 2012; Boksem & Smidts, 2015; Genevsky et al., 2017; Venkatraman et al., 2015). It remains an open question whether the same non-redundancy can also be observed for neural similarity.

We aimed at answering these questions with three fMRI studies. We examined whether neural responses, in terms of activation and similarity, predicted out-of-sample preference for videos. We then examined if these responses explained additional variance after taking into account self-reported preference of the participants. Finally, we provided more insight into the potential mechanism of neural similarity as an indicator of preference by looking into the covariation of moment-by-moment neural similarity and activation at the individual level.

4.3 Materials and Methods

We present results from three original studies. The first two involved the same set of 35 commercials (Study 1a and 1b), while the third involved 18 movie-trailers (hereafter Study 2; see Chapter 3 for more details), totaling 88 participants in the scanner. In all three studies, participants inside the scanner watched videos once in randomized order, followed by evaluation after each presentation (see Table 4.1 for an overview of the three studies). Our main dependent variable (DV) is out-of-sample preference reported by a separate and larger group of raters for each set of stimuli (117 raters for TV commercials and 96 raters for movie-trailers). For a subset of TV commercials (24 out of 35), we have obtained contemporaneous aided recall data collected by a marketing research company during the rollouts of the respective commercials, which serves as our secondary DV.

Table 4.1 Summary of studies

	Study 1a	Study 1b	Study 2
<i>Stimulus</i>			
N and type	35 previously broadcast TV commercials		18 previously unseen movie-trailers
Length (s)	25-60 (M=41; SD=9.4)		66-150 (M=134; SD=18.3)
<i>Dependent variable</i>			
Main: Out-of-sample preference	117 external raters on 2 items of 7-point Likert scale		96 external raters on an 11-point scale (5-star rating in half-star increments)
Secondary: Aided recall	Aided recall (%) by online panel at time of broadcast (for a subset of 24 commercials)		–
<i>Scanning participants</i>			
N	40	20	28
Mean age	35.1	39.1	20.9
Sex	56% female	55% female	50% female
<i>Scanning parameters</i>			
Scanner type	1.5T	3T	3T
Repetition time (TR)	3000ms	2140ms	2070ms

4.3.1 Experimental design and statistical analysis

Our approach to the three studies was (a) to investigate which brain areas were associated with out-of-sample aggregate preference using the first study (Study 1a), and (b) to replicate these findings with the second study (Study 1b). After locating the relevant brain areas in Study 1a and 1b, we extracted neural information from these regions from all three studies (Study 1a, 1b and 2), and investigated to what extent neural similarity information could

explain variance in aggregate preference. We then examined to what extent neural similarity in these regions explained additional variance on top of self-report measures and neural activation.

The studies were approved by the institutional review board in line with the Declaration of Helsinki. All participants signed informed consent prior to participation.

4.3.2 TV commercial study (Study 1a and 1b)

4.3.2.1 Stimuli

Thirty-five commercials from seven well-known telecommunication brands, aired on national TV networks during 2009-2015, were used as stimuli (see supplementary material S1 for details). Their lengths varied from 25s to 60s ($M_{\text{length}} = 40.5\text{s}$; $SD_{\text{length}} = 9.4\text{s}$). On average, the commercials appeared on air for 7.4 weeks ($SD_{\text{broadcast}} = 2.2$ weeks).

4.3.2.2 Main DV

Out-of-sample aggregate preference was measured by obtaining responses from 117 individuals not involved in the fMRI scanning ($M_{\text{age}} = 32.9$; $SD_{\text{age}} = 12.3$; 56% female). They watched the commercials in randomized order, and then gave a general evaluation ('how much did you like this video?') and rated them on four aspects on a 7-point Likert scale: whether they were entertaining, informative, relevant, and convincing. To find out if the five items measured the same latent construct, we used factor analysis, which revealed two factors – a first factor consisting of the general evaluation and the entertaining score, and a second factor with the remaining three items. Since the second factor involves more cognitive judgment instead of preference, we used the average of the general evaluation and the entertaining score as the liking score (responses to the two items were highly correlated, $r = .85$). Converting the score onto a 0-1 scale with a mid-point at .5, the

mean rating of the 35 commercials was .575 ($SD_{\text{rating}} = .115$, range = .322 – .697). (We present results of the analysis of the remaining items in supplementary material S2.)

4.3.2.3 Secondary DV

For a subset of commercials (24 out of 35), contemporaneous market level data on aided recall at the time of broadcast (2009-2015) were available. A marketing research company systematically tracked aided recall for each of the subset commercials over the duration of their broadcasts. In each given week when a certain commercial was aired, a fresh panel of 100 online respondents aged 16-65 drawn from a representative national sample saw a few screenshots of that commercial and were asked to report if they had definitely seen it, might have seen it, or did not recall seeing it in the past 4 weeks. Aided recall was the ratio of all respondents who reported having definitely seen the commercial during its entire broadcast period.

4.3.2.4 Participants and procedure

Participants (Study 1a: $N = 40$; $M_{\text{age}} = 35.1$; $SD_{\text{age}} = 9.7$; 56% female; Study 1b: $N = 20$; $M_{\text{age}} = 39.1$; $SD_{\text{age}} = 11.1$; 55% female) were recruited from the general public by a marketing research company. Potential subjects responded to an online MRI screening questionnaire which ensured they had no history of neurological illness or damage, were not using drugs or psychiatric medication, and had normal or corrected-to-normal vision. Those who were found suitable for scanning were contacted, and written informed consent was obtained in advance. For their participation, each participant was paid €60. They were invited to the scanning facility, where they watched the 35 commercials, presented in randomized order, during fMRI scanning. Immediately after each commercial, participants indicated their liking via button presses without time limit, then waited for 6-10s with a blank screen before another commercial began. (See supplementary material S3 for detailed task procedure.) The scanning lasted about 35 minutes. Within three

days after scanning, they completed an online survey which contained the same 5-item questionnaire for each of the commercials, again presented in random order. We used their responses to the same 2 items (entertaining and general evaluation) to compute their individual rating for each of the 35 commercials (in-sample preference).

4.3.2.5 FMRI acquisition

For Study 1a, the functional magnetic resonance images were obtained using a 1.5T (Siemens) MRI system. Functional scans were acquired by a T2*-weighted gradient-echo, echo-planar pulse sequence in ascending interleaved order (35 slices, 3.0 mm slice thickness, 0.6 mm slice gap, 3.0 × 3.0 mm in-plane resolution, 80 × 80 voxels per slice, flip angle = 90°). Echo time (TE) was 40ms and repetition time (TR) was 3000ms. A T1-weighted image was acquired for anatomical reference (1.0 × 1.0 × 1.0 mm resolution, 176 sagittal slices, flip angle = 15°, TE = 3.93ms, TR = 2040ms).

In Study 1b, a different scanner was used with modified acquisition parameters. The functional magnetic resonance images were obtained using a 3T (Siemens) MRI system. Functional scans were acquired by a T2*-weighted gradient-echo, echo-planar pulse sequence in ascending interleaved order (35 slices, 3.0 mm slice thickness, 0.6 mm slice gap, 3.0 × 3.0 mm in-plane resolution, 64 × 64 voxels per slice, flip angle = 90°). Different echo time (TE = 25ms) and repetition time (TR = 2140ms) were used. A T1-weighted image was acquired for anatomical reference (1.0 × 1.0 × 1.0 mm resolution, 192 sagittal slices, flip angle = 9°, TE = 2.98ms, TR = 2300ms).

4.3.3 Movie-trailer study (Study 2)

This study has been reported in Chapter 3. We presented a brief overview of the study below; for details, please refer to the previous text.

4.3.3.1 Stimuli

The stimuli were 18 movie trailers selected from a larger database of 168 movies (see supplementary material S1 for more details on movie trailers). In short, the movies were released in the US between 2000 and 2010 with varying levels of commercial success (box office receipts between \$4.4 million and \$121 million; $M_{\text{boxoffice}} = \$47$ million). The trailers of these movies are 66 to 150s long ($M_{\text{length}} = 134\text{s}$; $SD_{\text{length}} = 18.3\text{s}$). Importantly, a screening procedure during subject recruitment confirmed that none of the movies had been seen by any of the participants.

4.3.3.2 Main DV

Out-of-sample ratings were collected from a separate group of university students from the same population ($N = 96$) who watched the movie trailers in a randomized order. Immediately after each movie-trailer, they rated liking on a 5-star rating scale (from 0 to 5 stars in half-star increments). The average rating was 2.45 stars (range = 1.16 – 3.51 stars; $SD_{\text{star}} = 0.71$).

4.3.3.3 Participants and procedure

Thirty-one participants were recruited from the university population and paid a fixed fee of €10 per hour for their participation in the fMRI scanning session. Potential subjects responded to an online MRI screening questionnaire which ensured they had no history of neurological illness or damage, were not using drugs or psychiatric medication, and had normal or corrected-to-normal vision. One participant had to be excluded due to falling asleep, and two more due to excessive head movements. These are omitted from all behavioral and neural analyses. The final sample consisted of 28 participants ($M_{\text{age}} = 20.9$; $SD_{\text{age}} = 3.2$; 14 female).

Participants underwent fMRI scanning while watching the 18 movie trailers, presented in randomized order, together with one practice video at the

beginning (30s). For each movie-trailer, the poster of that movie appeared before and after the video for 3.5s. After that, they had to provide different ratings immediately after viewing, such as liking, willingness to pay, valence and arousal without time limit. A blank screen would appear for 3.5s before the next movie-trailer. (See supplementary material S3 for detailed task procedure.) We used their responses to the 5-star liking scale (same as the main DV) as in-sample preference for each of the movie-trailers.

4.3.3.4 FMRI acquisition

The functional magnetic resonance images were obtained using a 3T MRI system (Siemens). Functional data was acquired with a T2*-sensitized parallel imaging multi-echo sequence with echo times (TE) at 9, 19.3, 30 and 40 ms in ascending order (34 slices, 3.0 mm slice thickness, 0.5 mm slice gap, 3.5 × 3.5 mm in-plane resolution, 64 × 64 voxels per slice, flip angle = 90°). Repetition time (TR) was 2070ms. Prior to preprocessing, the four read-outs acquired via the multi-echo sequence were combined and realigned by using standard procedures described by Poser et al (2006). A T1-weighted image was acquired for anatomical reference (1.0 × 1.0 × 1.0 mm resolution, 192 sagittal slices, flip angle = 8°, TE = 3.03ms, TR = 2300ms).

4.3.4 Data preprocessing, extraction and visualization

We preprocessed the neuroimaging data using standard software (SPM12, Wellcome Department of Cognitive Neurology, London, UK). To correct for head motion, the functional images were realigned to the mean image. Functional images were slice-time corrected, coregistered to the anatomical image, spatially normalized to the Montreal Neurological Institute (MNI) template and lightly smoothed with a Gaussian kernel (3 × 3 × 3 mm full width at half maximum). In all studies, we verified that acquired images cover the whole brain, including cerebellum (supplementary material S4). Whole-brain activation analysis was conducted with SPM12. Neural similarity analysis was conducted with the PyMVPA toolbox (Hanke et al.,

2009) and custom Python scripts. In both cases, spatially normalized neuroimaging data were regressed with average global signals and white matter signals. A high-pass filter implemented by discrete cosine transform (1/128Hz for TV commercials and 1/256Hz for movie-trailers) was applied, and each voxel was z -scored within the scanning session. We extracted brain volumes during stimuli viewing between 3s after stimulus onset and 3s after stimulus offset. To ensure the onset time relative to the acquisition time of the first extracted volume was the same across participants, temporal interpolation between volumes was carried out. Resultant brain maps are visualized using the Caret software (Van Essen et al., 2001), with additional images produced by Nilearn (Abraham et al., 2014).

4.3.5 Calculating neural similarity

We calculated neural similarity for each stimulus as follows (Figure 4.1). For a stimulus v seen by n participants, we had spatiotemporal matrices $M_{v,1} \cdots M_{v,n}$, each with t volumes \times k voxels. Scaling was first performed by subtracting the mean (voxel-wise) and then dividing by the matrix norm (i.e., the root of sum of squares of all elements) within each matrix. The neural similarity s_v of that stimulus is defined as the negative of the average pairwise Euclidean distance (i.e., the root of sum of squares of differences of all elements) of matrices $M_{v,1} \cdots M_{v,n}$, i.e.,

$$s_v = -\frac{2}{n(n-1)} \sum_{i=1}^n \sum_{j=i+1}^n \|M_{v,i} - M_{v,j}\| \quad (1)$$

4.3.6 Whole-brain analysis of neural similarity

To create whole-brain maps of neural similarity for each stimulus, we used the searchlight approach, employing a spherical searchlight of 2-voxel radius ($k = 33$ voxels). At each voxel, we extracted from participants the spatiotemporal matrices of neural responses using the spherical searchlight

mask, then calculated neural similarity using the above equation (Equation 1). Each stimulus had therefore a whole-brain similarity map.

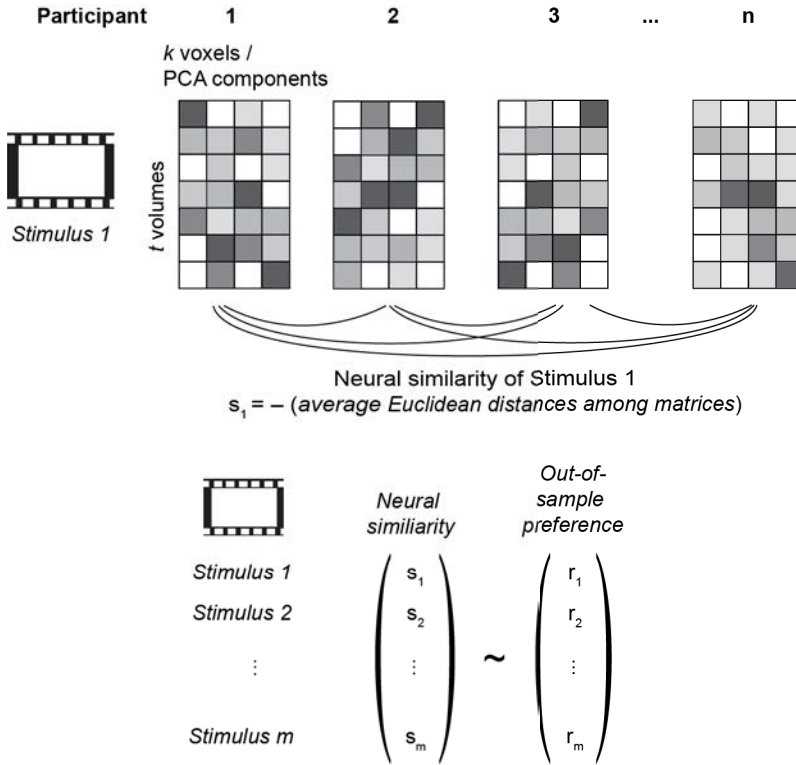


Figure 4.1 Schematic diagram of neural similarity calculation

In order to determine which brain areas had a significant similarity score during stimulus presentation (i.e., exhibited synchronized neural activities across participants), we implemented the following testing procedure: As we calculated the inter-subject pairwise distances ($-\|M_{v,i} - M_{v,j}\|$, for a given pair of participants i and j) for each stimulus v , we also randomly rolled one of the matrices along the time-axis ($M_{v,j}^*$) then calculated the similarity ($s_{v,null}$) again under this null condition ($-\|M_{v,i} - M_{v,j}^*\|$). Out of the $\frac{1}{2}n(n-1)$ inter-subject pairwise distances, a paired t -test ($s_v - s_{v,null}$) was conducted at each voxel for each stimulus. The t maps were then averaged across stimuli.

To investigate whether neural similarity correlates with out-of-sample preference, we calculated at each voxel a Pearson's correlation while partialling out stimulus length to minimize potential confounding effect of time. Similarly, we estimated statistical significance by permutation testing. We shuffled the stimuli ratings 10,000 times and obtained null correlation maps, then derived the empirical p value at each voxel from the voxel's own null distribution.

4.3.7 Whole-brain analysis of neural activation

To study the relationship between neural activation and out-of-sample preference, we estimated for each participant a general linear model (GLM) containing the following: a boxcar regressor to indicate whenever a video was presented, and an additional parametrically modulated regressor of out-of-sample preference. The design matrix was then convolved with canonical hemodynamic response function (HRF), and average global signal and white matter signal were entered as regressors of no interest. Based on these estimated beta images, second-level random-effects group contrast maps were then created in both directions (i.e., positive and negative correlation between activation and out-of-sample preference).

4.3.8 Region-of-interest (ROI) analysis of neural similarity and activation

Having identified voxels in whole-brain analysis, we proceeded to use the areas identified in Study 1a and 1b as regions-of-interest (ROIs) and recalculated neural similarity and activation. Given the high spatial correlation among voxels, we first reduced the data dimension by conducting principal component analysis (PCA) on time series data from Study 1a. Specifically, we concatenated ROI-extracted fMRI time series from all 40 participants, choosing only sections where the stimuli were presented (mean-centering was done within each stimulus), resulting in a time series of 20,680 volumes. The first 100 PCA components (explaining 62.8% of the total

variance) were selected. Component weights obtained in Study 1a were used to transform the data in Study 1b and 2. (Additional PCA analyses showed component weights obtained within each dataset were highly similar.) Neural similarity was calculated using the Euclidean distances of the PCA-transformed matrices (t volumes \times 100 components, c.f. Equation 1). Same as in whole-brain analysis, neural similarity and activation scores were first adjusted for stimulus length (obtaining residuals by regression) to minimize potential confounding effect of time.

Knowing that the ROIs were themselves derived from the results obtained in Study 1a and 1b, we then attempted to replicate the effect with secondary DV (aided recall) and a new set of stimuli (Study 2). We also entered neural similarity, neural activation and in-sample preference into a regression model to see if neural similarity provides a unique contribution in explaining the variance of out-of-sample preference.

4.3.9 Robustness analysis on neural similarity calculation

Calculation of neural similarity involves determining the number of PCA components and the choice of distance metric. We have redone the analysis using 50 and 200 components (accounting for 45% and 82% of the total variance, respectively), and also untransformed raw voxels; we have also tested different distance metrics (cosine and city block).

4.3.10 Code accessibility and data availability

The data that support the findings of this study, including preprocessing and analysis scripts, are available in an open repository¹⁰.

¹⁰ https://github.com/chanhangyee/neural_similarity

4.4 Results

Since we did not have *a priori* assumptions about whether, or where, we might find (a) significant neural similarity during stimulus presentation, and (b) significant relationship between this neural similarity and out-of-sample aggregate preference, we first conducted a whole-brain analysis on Study 1a. We then repeated the analysis on Study 1b. With a conjunction analysis of Study 1a and 1b, we located brain regions where neural similarity was found to have a significant effect on out-of-sample aggregate preference. We then extended the analysis, using the brain areas identified in Study 1, to a different stimulus type (Study 2). For neural activation, we repeated the same approach (whole-brain analysis and conjunction analysis in Study 1a and 1b, then replication in Study 2). (Scatterplots and correlations of variables are shown in supplementary material S5.)

4.4.1 Synchronized neural activities during video viewing

Similar to previous studies of video viewing, we observed synchronized neural activity at visual and auditory cortices, as well as superior temporal cortex, anterior and posterior cingulate cortices and cerebellum (Figure 4.2). In addition, amygdala and thalamus also displayed synchronized neural activity. Results found in both Study 1a and 1b were largely comparable; the resultant t maps from the two studies were highly correlated ($r = .905, p < .001$). These areas were also highly similar to past studies involving naturalistic stimulus viewing (Lahnakoski, Jääskeläinen, Sams, & Nummenmaa, 2017; Nummenmaa et al., 2012).

4.4.2 Neural similarity and activation correlate with out-of-sample preference

With whole-brain analysis of the TV commercials (Study 1a), we located anatomical areas where neural similarity and activation correlated with out-

of-sample aggregate preference. We then replicated the findings in Study 1b, and further tested the robustness with movie trailers in Study 2.

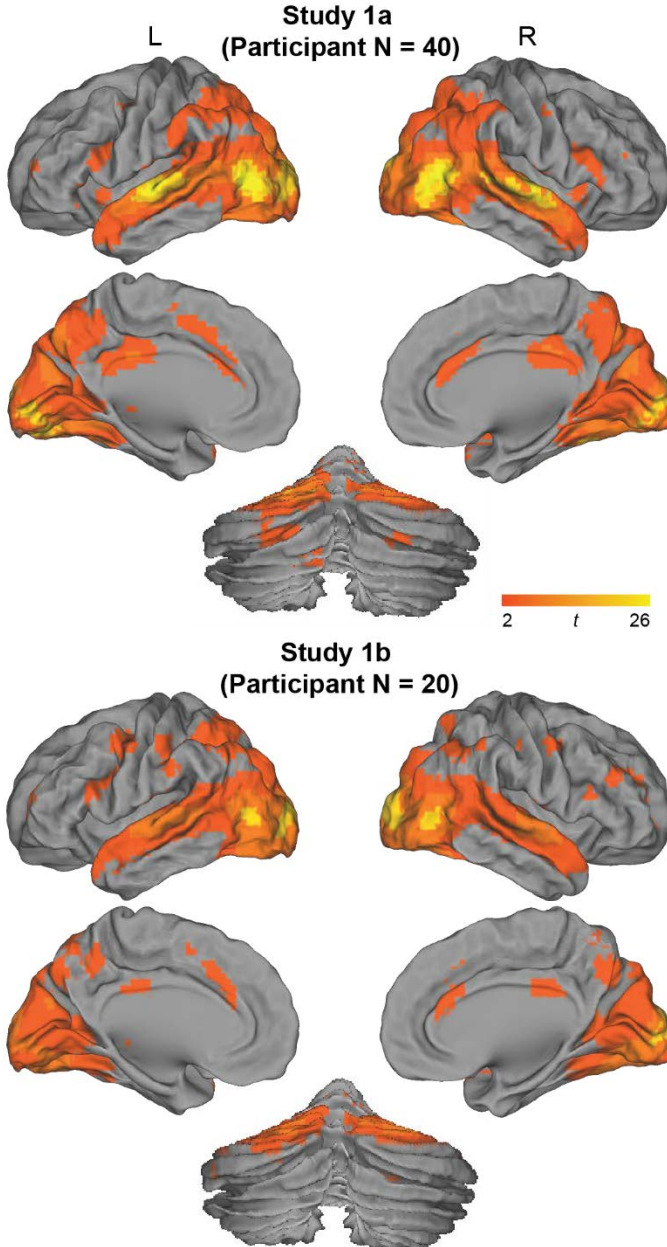


Figure 4.2 Brain regions showing significant synchronized activities, $p < .05$ FDR corrected

4.4.2.1 Whole-brain analysis

We investigated if there were brain regions where neural similarity in spatiotemporal neural patterns during video watching covaried with out-of-sample aggregate preference. We conducted whole-brain analysis in both Study 1a and 1b, then obtained an intersection of the thresholded statistical maps ($p < .05$ FDR corrected) to look for conjunction voxels (Nichols, Brett, Andersson, Wager, & Poline, 2005). Conjunction analysis revealed that neural similarity at bilateral temporal poles (TPs), temporoparietal junctions (TPJs) and cerebellum was positively associated with out-of-sample aggregate preference (Figure 4.3, top panel). Conjunction of significant brain areas from Study 1a and 1b encompasses 653 voxels, or 21.2cm³ (Table 4.2, top panel). In other words, when participants showed more similar spatiotemporal neural patterns at those regions during watching of a certain video, that video tended to be more preferred by out-of-sample raters. Largely overlapping results were found between Study 1a and 1b, and the resultant Fisher-transformed z maps were highly correlated between the two studies ($r = .561$, $p < .001$), despite the fact that the two studies differed in scanner type (1.5T vs 3T) and repetition time (3.0s vs 2.14s).

Conjunction analysis of the whole-brain activations in Study 1a and 1b revealed regions where stronger neural activation among participants was associated with greater out-of-sample aggregate preference (Figure 4.3, bottom panel). Significant voxels were found in bilateral superior temporal gyri (STG), as well as precuneus and the left inferior frontal cortex (pars triangularis, Broca's area). Conjunction of significant brain areas from Study 1a and 1b encompasses 723 voxels, or 23.4cm³ (Table 4.2, bottom panel). The resultant group contrast z maps were again highly correlated between the two studies ($r = .624$, $p < .001$). In a supplementary analysis we performed a significance test on both similarity and activation conjunction sizes by permutation (see supplementary material S6 for details).

Table 4.2 Coordinates and sizes of conjunction clusters

Similarity (Study 1a \cap 1b)	Cluster size		Cluster center		
	in voxel	in cm ³	<i>x</i>	<i>y</i>	<i>z</i>
Temporal Pole R	229	7.42	52	-5	-21
Temporal Pole L	172	5.57	-54	-53	12
Temporoparietal Junction L	165	5.35	-49	9	-28
Cerebellum R	56	1.81	23	-76	-35
Cerebellum L	11	0.36	-23	-75	-32
Temporal Mid L	9	0.29	-49	-25	-8
Temporal Mid R	7	0.23	57	-52	17
Activation (Study 1a \cap 1b)	Cluster size		Cluster center		
	in voxel	in cm ³	<i>x</i>	<i>y</i>	<i>z</i>
Superior Temporal Gyrus R	338	10.95	53	-31	2
Superior Temporal Gyrus L	304	9.85	-53	-36	4
Precuneus	172	5.57	0	-54	40
Frontal Inf Tri L	9	0.29	-49	19	18

4.4.2.2 ROI analysis

We examined to what extent neural information, in terms of both activation and similarity, could predict out-of-sample aggregate preference for different stimuli (movie-trailers). Selecting the voxels in the conjunction areas of the two TV commercial studies (i.e., red in Figure 4.3 top panel encompassing bilateral TP, TPJ and cerebellum; and blue in Figure 4.3 bottom panel encompassing STG and precuneus), we re-calculated neural similarity (using the red voxels) and activation (using the blue voxels) for the third dataset involving movie-trailers (Study 2). (For the sake of completeness, the whole-brain analysis on Study 2 is included in supplementary material S7.)

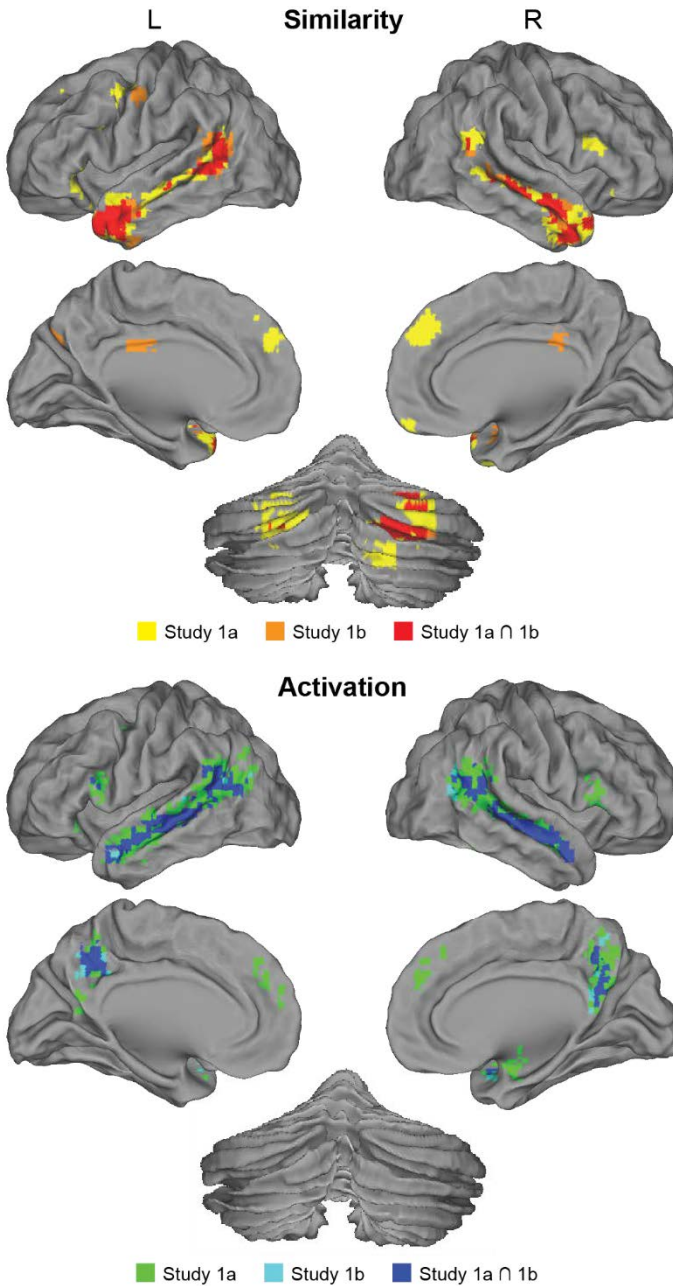


Figure 4.3 Voxels with significant correlation between neural similarity and out-of-sample preference (top); and between neural activation and out-of-sample preference (bottom), $p < .05$ FDR corrected

1. Whole-brain analysis — Locating voxels which covary with main DV

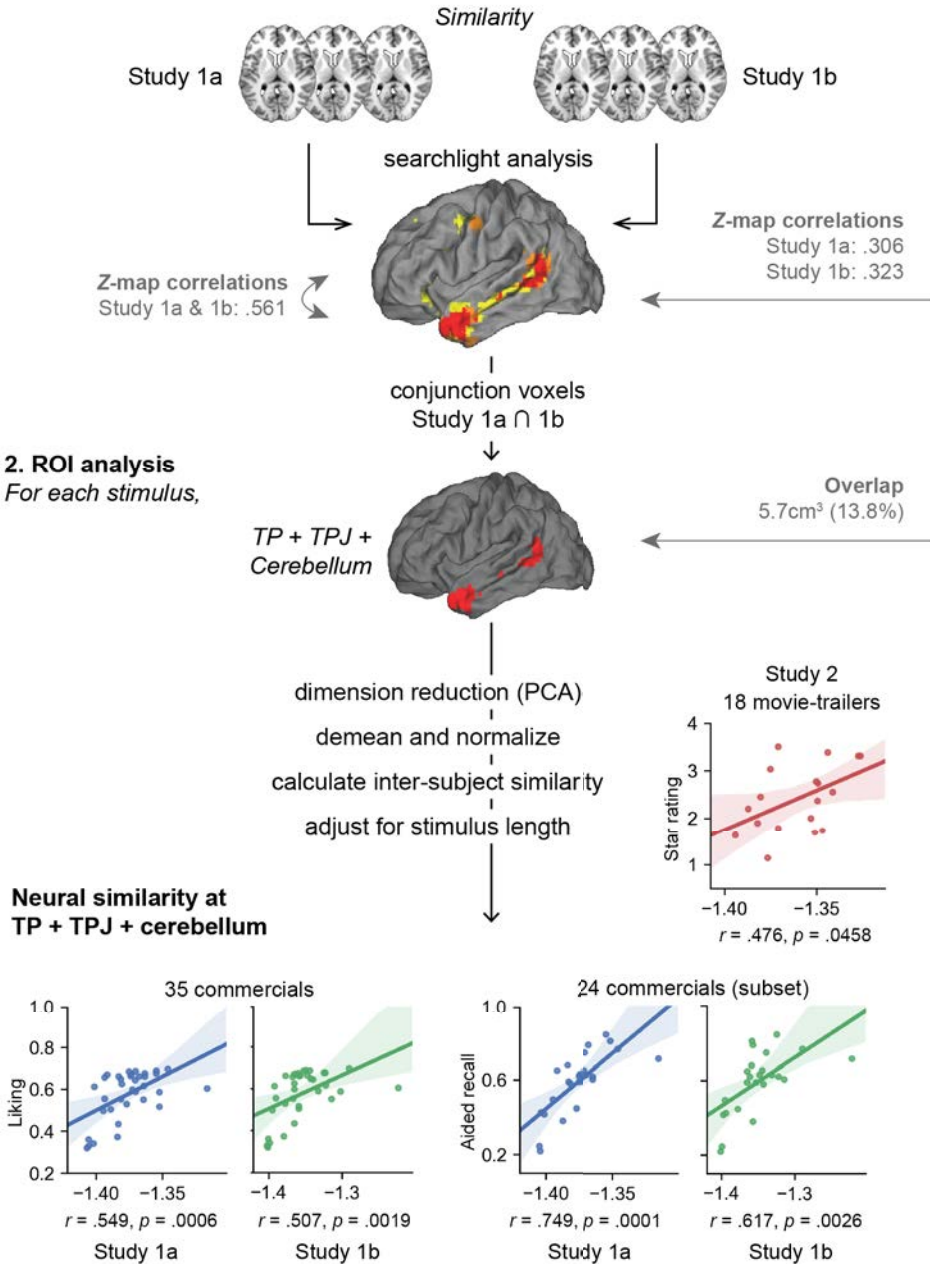
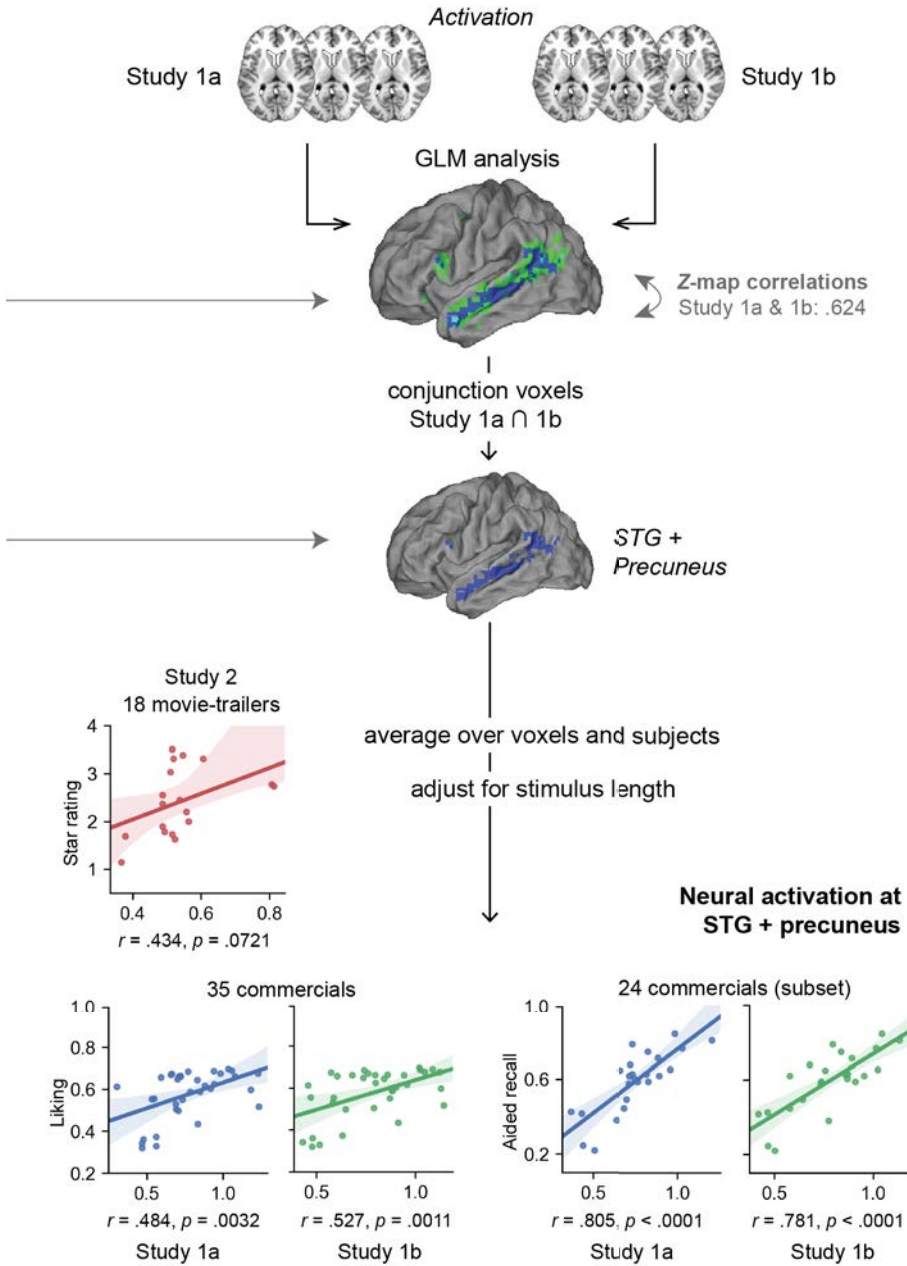


Figure 4.4 Schematic diagram of analysis and summary of results



Across the three studies, neural similarity at TP/TPJ/cerebellum correlated with out-of-sample preference. Notably, the effect was robust for using different stimuli (movie-trailers) using the voxels identified in TV commercials. Correlation between neural activation at STG/precuneus and out-of-sample preference for the movie-trailers were similar to the commercials ($r = .434$), but just failed to reach the .05 significance level, $p = .072$. We also extended the findings to a market level DV, i.e., aided recall, for a subset of TV commercials. Both neural similarity in TP/TPJ/cerebellum and activation in STG/precuneus correlated with aided recall ($r = .617 - .805$, all $ps < .005$, see Figure 4.4 for a summary of findings).

In a supplementary ROI analysis (supplementary material S8), we did not obtain a consistent relationship between out-of-sample preference and activation at known subjective valuation areas, such as amygdala, anterior insula, anterior cingulate cortex (ACC), mPFC and NAcc (Bartra et al., 2013; Samanez-Larkin & Knutson, 2015).

Robustness analysis (supplementary material S9) shows that findings were robust to changing both PCA component number and metric choice. In addition, our neural similarity measure incorporates all voxels from the bilateral regions of TP, TPJ and cerebellum. To understand the importance of individual areas, we calculated neural similarity for each separate cluster (using raw voxels instead of component weights) and found similar results (see supplementary material S10), underlining the role of each of the three areas in the processing and evaluation of videos.

To illustrate how neural similarity differs between stimuli of high and low out-of-sample preference, Figure 4.5 shows the time-course plots of the most- and least-liked stimuli using the first two PCA components.

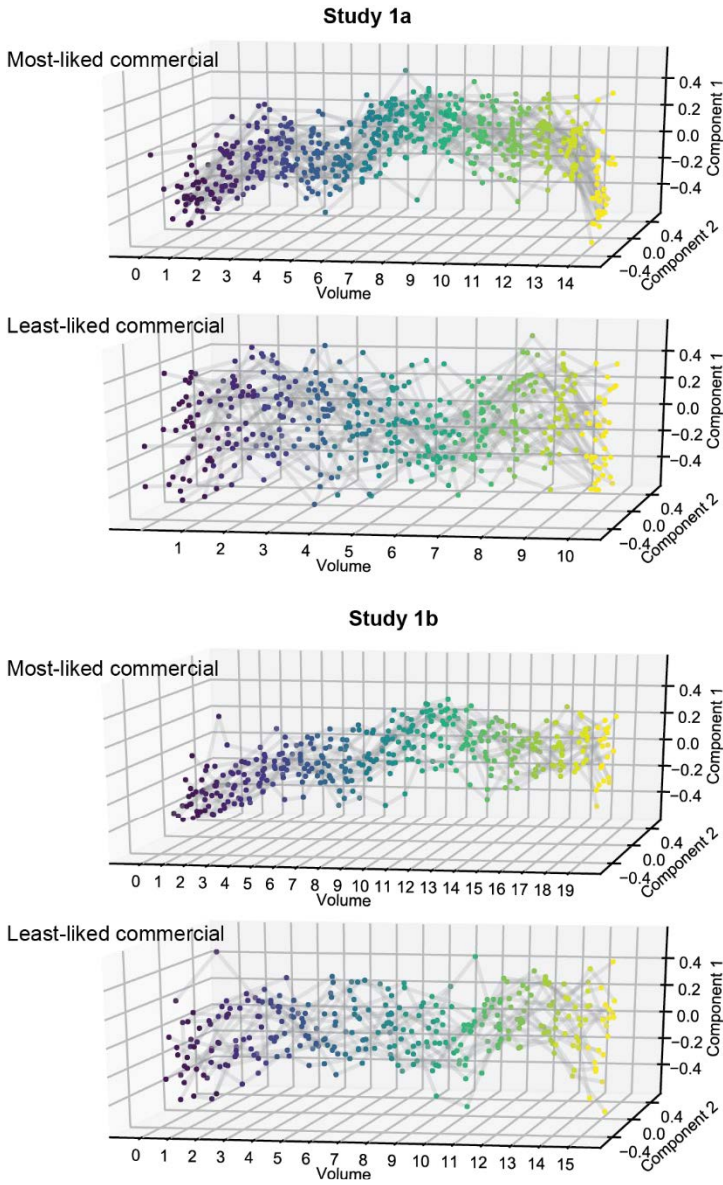


Figure 4.5 Time-course plots of neural activities at TP/TPJ/cerebellum for most- and least-liked commercials

4.4.3 Additional variance in out-of-sample preference explained by neural signals

Next, we examined whether neural similarity and activation provided distinct information in addition to in-sample self-report preference in predicting out-of-sample preference (Table 4.3). We combined results from the three studies and conducted mixed-effect regression models, using study as random intercept. We compared a reduced regression model with stimulus length and self-report preference entered as regressors (Model 1), and a full model with the additional neural regressors. When either neural similarity (Model 2) or activation (3) or both (4) were entered into the regression model, model performance improved significantly, showing that both neural similarity and activation independently contribute to improved prediction of out-of-sample preference, above and beyond in-sample self-reported preference.

Table 4.3 Mixed-effect regression models predicting out-of-sample preference with different regressors, with study entered as random intercepts.¹¹

	(1)		(2)		(3)		(4)	
	β	p	β	p	β	p	β	p
Video length	0.238	.001	0.339	<.001	0.197	.001	0.261	<.001
In-sample preference	0.686	<.001	0.522	<.001	0.558	<.001	0.499	<.001
Neural similarity			0.288	<.001			0.153	.028
Neural activation					0.331	<.001	0.257	<.001
AIC	158.1		142.1		132.9		130.1	
χ^2			18.0	<.001	27.2	<.001	32.0	<.001

¹¹ Model comparisons were done with the baseline model (1). Numbers of stimuli are 35 for both Study 1a and Study 1b, and 18 for Study 2.

4.4.3.1 Potential confounding effects of previous exposure and memory for TV commercials

In Study 1a and 1b, like a previous study (Dmochowski et al., 2014), we used previously broadcasted materials. Contemporaneous aided recall data might be confounded by the size of the advertising campaigns at that time (such that bigger campaigns had more media exposure thus might lead to higher recall in the population); current out-of-sample preference might be confounded by the campaign size, and the time lapsed since first exposure (such that more recently broadcast commercials might be liked more). We attempted to find out their potential effects by repeating the analysis with two additional regressors: weeks since initial broadcast, and gross rating points for age group 20-49 (i.e., number of cumulative impressions as a percentage of target population during the advertising campaign). Regression results were robust to the two additional regressors (see supplementary material S11).

4.5 Discussion

Across different participants, scanning parameters, video lengths and types, we uncovered neural information that predicted out-of-sample aggregate preference of naturalistic dynamic stimuli. With respect to the research questions set forth in the introduction, we present the following findings:

4.5.1 Neural similarity in the TP, TPJ and cerebellum predicts out-of-sample preference

We found that the synchronized neural activity across participants at the TP, TPJ and cerebellum was associated with out-of-sample preference for videos, in terms of liking and recall. TP and TPJ have been described as the association cortex (Olson, Plotzker, & Ezzyat, 2007), due to their extensive connections with the sensory systems. TP is interconnected with the

amygdala and orbital frontal cortex, and the suggested role of TP as a midway station between multi-modal perceptual inputs and emotional responses (Wong & Gallate, 2012) is consistent with our current findings that video watching evoked similar neural responses in these areas. A meta-analytic review of activation-based studies also found the involvement of bilateral temporal poles in the evaluation of emotional content from stimuli (Lindquist, Wager, Kober, Bliss-Moreau, & Barrett, 2012). TPJ, on the other hand, has been linked to multiple functions pertinent to the emotional processing of complex stimuli, from general cognitive functions (e.g., attention, language processing, and episodic memory encoding) to more selective ones (e.g., mentalizing and social cognition) (Carter & Huettel, 2013).

In the smaller body of literature on neural similarity, right TP was found to be part of the brain network whose inter-subject synchronicity covaried with self-report arousal during film watching (Nummenmaa et al., 2012), while left TP synchronicity correlated with syntactic complexity during story listening (Brennan et al., 2012). There is also evidence that neural activities at TPs and TPJs during narrating and listening to the same story are synchronized (Silbert et al., 2014); more interestingly, neural similarity at TP and TPJ has previously been found to predict successful content recall after watching a video (Hasson et al., 2008). In brief, neural similarity at those areas may signal engagement and effective/successful communication.

Lastly, the inclusion of cerebellum in our findings provides further evidence on its role in emotional processing (Schmahmann & Caplan, 2006). In fact, a number of studies found the involvement of cerebellum during video watching (Franklin & Adams, 2011; Han et al., 2011; Mathiak & Weber, 2006). We considered the possibility that synchronized cerebellar activities might be driven by perceptual processes such as eye movement. In a supplementary analysis (supplementary material S12), we compared activation maps associated with movement and emotion obtained from Neurosynth (Yarkoni et al., 2011), and found that the cerebellum ROI in the

current study contains voxels included in the emotion-related association map but not the movement-related map, suggesting that the effect is likely to be driven by emotional processing at cerebellum.

In the current study, we revealed for the first time that neural similarity at TP, TPJ and cerebellum within a small group can predict out-of-sample preference. This finding, together with the fact that we found no significant effect in sensory or prefrontal cortices, suggests that aggregate preference of the population may be related to the interpersonal consistency in higher-order comprehension, instead of sensory processing or valuation. This echoes past findings on neural activation that, while video advertisements with more attention-grabbing features produced higher activation in occipital cortex, they were associated with decreased activation in temporal and prefrontal cortices, and lower recall rate (Langleben et al., 2009).

4.5.2 Neural activation in the STG and precuneus predicts out-of-sample preference

In addition to our findings on neural similarity, we found that neural activation at STG and precuneus consistently predicted preference across stimulus types. Precuneus is known to be associated with self-consciousness (Cavanna & Trimble, 2006) and valuation (Litt, Plassmann, Shiv, & Rangel, 2011). On the other hand, the role of STG in the integration of sounds and images in audiovisual stimuli, especially those involving speech, is well-documented (Beauchamp, Argall, Bodurka, Duyn, & Martin, 2004; Noesselt, Bergmann, Heinze, Münte, & Spence, 2012). One plausible interpretation may be that preference is related to attention, which in turn modulates STG activation during audiovisual integration (Morís Fernández, Visser, Ventura-Campos, Ávila, & Soto-Faraco, 2015). On the other hand, precuneus has long been associated with self-consciousness (Cavanna & Trimble, 2006), and a recent study suggested it may also have a role in attention (Klasen, Weber, Kircher, Mathiak, & Mathiak, 2012). These findings point to the speculation that neural activation in STG and

precuneus may be an indication of engagement, although further study is needed before any definitive conclusion can be drawn.

Our study did not find activation at known subjective valuation areas, such as amygdala, anterior insula, anterior cingulate cortex (ACC), mPFC and NAcc (Bartra et al., 2013; Samanez-Larkin & Knutson, 2015) to be predictive of out-of-sample preference. Among studies involving dynamic stimuli, there are conflicting findings on the relationship between self-report enjoyment and activation in these areas. For example, the amygdala was found to correlate with liking in comedy movies (Franklin & Adams, 2011; Jääskeläinen et al., 2016) and TV commercials (Venkatraman et al., 2015), while no such effect was found for liking of dance video clips (Cross, Kirsch, Ticini, & Schütz-Bosbach, 2011). In one study, decreased mPFC activity was related with humor rating of comedy videos (Franklin & Adams, 2011), while increased NAcc activity was found to predict market-level success of songs (Berns & Moore, 2012) and TV commercials (Venkatraman et al., 2015) but not in others that measured self-report liking (Cross et al., 2011; Franklin & Adams, 2011; Jääskeläinen et al., 2016). Overall, it seems that activations at brain areas traditionally associated with reward such as NAcc and mPFC may not offer a reliable signal of out-of-sample preference for dynamic stimuli.

4.5.3 Overlap in ROIs associated with similarity and activation

While studies on neural similarity and activation often identify different but overlapping brain regions involved in the same task or observation (e.g., Hasson et al., 2008; Nummenmaa et al., 2014), it is unclear whether the similarity- and activation-based measurements offer the same or distinct information. In a supplementary analysis (supplementary material S13) we computed both similarity and activation within each individual ROI and found that both similarity and activation in the temporal lobe (TP, TPJ and STG) predict out-of-sample preference, while only similarity (but not activation) measured at cerebellum and only activation (but not similarity)

measured at precuneus predicts out-of-sample preference. These findings are perhaps not that surprising, given the close proximity of the ROIs situated in the temporal lobe, and the smoothing kernel used in preprocessing of the data. Importantly, they do not take away from the result that there is unique information in similarity measures that is not present in activation measures (see Table 4.3), even if similarity and activation are observed in the same/similar brain areas. Indeed, the finding that aggregate preference can be predicted from similarity and activation in areas that are at least partly distinct supports the view that information from pattern similarities and magnitude differences may have separate neural substrates.

4.5.4 Neural similarity as a distinct information source

We replicated past findings that neural activation offers unique information about aggregate preference in addition to self-report responses (Berns & Moore, 2012; Boksem & Smidts, 2015; Genevsky et al., 2017; Venkatraman et al., 2015). Here, we showed that neural similarity also provides unique information, above and beyond self-report. As such, it adds to the growing literature of neural prediction which demonstrates that brain imaging provides additional predictive power on top of self-report measures.

Why does neural similarity from a group of individuals improve out-of-sample preference prediction, even after taking into account the stated preference of those individuals? We posit that similar to the case of neural activation (Knutson & Genevsky, 2018), neural similarity may capture aspects of individual choice that scale better to forecast aggregate choice. Specifically, neural similarity at TP/TPJ/cerebellum may measure the level of sustained engagement with the videos, which results in enhanced understanding of the content ('I understand what the video is about'), one of the components for liking that may generalize more across individuals compared to more idiosyncratic components such as personal values ('I find the video suits my needs/tastes').

4.5.5 Measuring spatiotemporal similarity in neural activities

Unlike many studies on temporal synchronization of brain activities (Golland et al., 2017; Hasson, 2004; Lankinen et al., 2014, 2018; Nummenmaa et al., 2012; Silbert et al., 2014), we did not compute our neural similarity measure using single-voxel time series. Instead, we made use of BOLD signals spanning across both space and time to calculate a multi-voxel, spatiotemporal similarity measure. We believe that this type of approach is particularly well suited for analysis of neural responses when complex, dynamic stimuli are involved. In a supplementary analysis, we indeed found that using single-voxel time series to compute neural similarity failed to uncover significant brain areas, and we observed similar anatomical findings with varying searchlight radius. (Results are available upon request.)

Discussions about ways to find out the optimal shape and size of searchlight for this type of multi-voxel analysis have not reached a consensus yet (Etzel, Zacks, & Braver, 2013), and it is likely to be dependent on the nature of the stimuli and the task. Further research is required to determine the best practice.

4.5.6 Further research questions

To further extend this line of research, there are two questions that would be of interest. First, can neural similarity be applied to static stimuli (i.e., spatial instead of spatiotemporal similarity)? Recent advances in representational similarity analysis (Kriegeskorte et al., 2008) allow researchers to apply this kind of analysis in studies involving consumer ratings or choosing products based on static stimuli. Second, beyond aggregate preference, can neural similarity predict actual choices made by consumers in the market (as measured by, for example, sales)? Again, more data on market-level effectiveness is needed before we understand the potential and limits of neural similarity.

Lastly, our three studies used video stimuli (TV commercials and movie trailers) originally designed to appeal to a broad audience. While we found that popular videos were the ones which evoked most similar responses among individuals, it is unclear if such findings are restricted to a certain genre of stimuli. For example, one may speculate that for cultural products meant to provoke discussion and stimulation (such as documentaries or debates), neural *dissimilarity* may actually be a more suitable predictor of preference.

4.5.7 Conclusion

In summary, across multiple studies we found that neural similarity is a robust signal of preference, and that it provides meaningful information in addition to both neural activation and self-report measures. This study provides several novel contributions. First, we found that neural similarity at temporal lobe and cerebellum – areas involved in sensory integration and emotional processing – predicted out-of-sample preference. Second, while prior research demonstrated the link between neural similarity and preference, this is the first study that demonstrates its robustness across scanning settings, outcome measurements and video types. Third, it showed the additional predictive power of neural similarity above and beyond self-report measures, and showed the value of harnessing this measure for the purpose of ‘neuroforecasting’ (Knutson & Genevsky, 2018). More research is needed in order to shed light on the interplay between activation and similarity within an individual. Whether the predictive effect of neural similarity on aggregate preference is specific to a certain type of stimuli (e.g., genre catered to mass entertainment) remains to be studied.

Chapter 5

Conclusion

In the preceding empirical chapters, I demonstrated multiple efforts to extract and analyze neural representations of consumer experience. The studies have shown that neural representations can reveal nonverbal consumer experience (brand image in Chapter 2); provide moment-by-moment descriptions of dynamic consumer experience (movie watching in Chapter 3); and improve predictions on market outcomes (population preference of TV commercials in Chapter 4). In this final chapter, I will discuss the theoretical and empirical contributions of the findings, take note of the limitations and point out future research directions.

5.1 Theoretical contributions to consumer neuroscience

Below I will detail several theoretical contributions to consumer neuroscience by the studies in the dissertation.

5.1.1 Consumer experience can be uncovered from spatiotemporal neural patterns

Over the three different studies, we have shown that spatiotemporal BOLD signal patterns obtained from fMRI scanning contain information about consumer experience in various contexts, from visualizing brand image to

watching videos. While early studies of neural representations began with mapping out the encoding of sensory information such as objects and sounds (De Martino et al., 2008; Haxby et al., 2001; Haynes & Rees, 2006; Kay, Naselaris, Prenger, & Gallant, 2008), researchers soon found success in uncovering distinct spatial patterns involved in higher-order mental processes in the brain, such as semantic (Charest & Kriegeskorte, 2015), affective (Saarimäki et al., 2018) and reward (Kahnt, 2018) representations.

Much of consumer psychology is concerned with the interaction between multi-sensory percepts (marketing materials) and abstract psychological constructs (value, motivation, emotion, knowledge). The studies in this dissertation demonstrate the feasibility of uncovering neural representations of consumer experience, either in real-time (watching narrative-rich videos) or reconstructed in the mind (visualizing brand image), without overt behavior or self-report. Based on various pattern analysis techniques, these neural representations offer rich, multi-dimensional knowledge about consumer experience. The findings provide a roadmap for future studies that further explore the application of multivariate pattern analysis of neuroimaging data in studying consumer experience.

5.1.2 Template-based decoding maps out content of consumer experience

As mentioned in Chapter 1, the bulk of consumer neuroscience research has been about understanding mechanisms of consumer decision-making and improving behavioral predictions through comparisons of activation intensities between experimental conditions. Efforts to access mental content based on neuroimaging data have been limited so far (e.g., Y.-P. Chen et al., 2015). One of the obvious difficulties is that spatial activation patterns of the brain do not by themselves have inherent meaning. Inferring mental content thus requires an extra step of translation.

In the studies of this dissertation, we pioneered a template-based approach to tackle this problem. Namely, we first obtain neural patterns related to a series of (relatively) unambiguous stimuli (social pictures in Chapter 2, or affective pictures in Chapter 3). The idea is to create a ‘decoding space’ by collecting a group of neural patterns that are already tied to meaningful concepts (the so-called templates), either within the individual or shared among a group. We then capture neural patterns in the focal consumer experience, and infer meanings based on their relations with the constellation of these neural pattern templates. Such an approach proved to be fruitful in our studies of brand image and emotional responses to videos. In addition, it should be noted that the decoding spaces are different in each of the studies, underlining the potential flexibility afforded to researchers and practitioners by this approach. So long as the template stimuli are able to evoke stable spatial representations in the brain (within or across individuals), they are considered suitable candidates for building the decoding space, upon which the meaning of subsequent consumer experience can be inferred. The findings from this dissertation will hopefully lay the groundwork for the expansion of consumer neuroscience from resolving ‘how consumers use their mind’, to focusing on ‘what consumers have in mind’. This will enable consumer neuroscience researchers to answer questions that are more pressing or pertinent to marketing practitioners.

5.1.3 Group similarity in brain responses reflects quality of consumer experience

Over different studies (Chapter 2 and 4), we found that group similarity contains information about the quality of the consumer experience. In Chapter 2, brands with a stronger image evoked more consistent spatial neural responses amongst consumers. In Chapter 4, videos of a higher quality (in terms of higher recall rate and self-report liking) also evoked more consistent spatiotemporal neural responses amongst consumers. More importantly, analysis of neural similarity was not redundant compared with

standard activation analysis and supplemented self-report ratings in making market-level predictions.

These findings echo a growing interest in studying inter-subject correlation in neural responses (Nastase et al., 2019). The idea behind the concept of neural similarity is straightforward: Successful communication is evidenced by the alignment of neural responses among receivers (Ames, Honey, Chow, Todorov, & Hasson, 2015). Intuitively, an effective brand communication should be able to make uniform impressions in consumers; likewise, a captivating video should be able to make viewers tune in and emotionally react in similar fashion.

While previous literature hint at this possibility with studies involving video-watching (Barnett & Cerf, 2017; Dmochowski et al., 2014), we locate the neural substrates (video watching in Chapter 4) and extend the findings to reconstructed, static consumer experience (visualizing brand image in Chapter 2). Thus, this dissertation provides evidence that consumer response consistency at the neural level can be a unique indicator of the quality of consumer experience, and by extension that of marketing actions. It opens up a new line of research on understanding the marketing implications of consumer response consistency at the neural level.

5.2 Implications for marketing practitioners

In the preceding chapters, I have detailed various practical implications in each of the studies. Here I will generalize some of the observations across the studies that could be useful for marketing practitioners.

For neuromarketing practitioners, this dissertation underlines the potential of applying machine learning in analysis of brain measurements. In particular, practitioners should find ways to leverage on the information obtained from the above-mentioned template-based content decoding and neural similarity analysis. Since the predominant method in commercial practices is EEG,

recent academic research is also showing similar efforts on multivariate analysis in this modality (Eijlers et al., 2019; Hakim & Levy, 2019). Moreover, the studies in this dissertation also offer valuable pointers for EEG research. For example, we found that the temporal cortex, ranging from the more posterior part of the temporoparietal junction to temporal pole, holds certain information on the quality of consumer experience, especially when involving audiovisual materials (Chapter 3 and 4), which is also consistent with past studies using TV commercials (Couwenberg et al., 2017; Dmochowski et al., 2014). Targeting recordings from electrodes covering this region may improve overall signal quality when conducting similar studies in EEG, such as using neural similarity to predict video popularity (Barnett & Cerf, 2017).

For marketing practitioners, the idea of deploying neuromarketing can be both tantalizing and disorientating, given past hypes and controversies (Levallois, Smidts, & Wouters, 2019). The studies in this dissertation offer distinct examples where consumer neuroscience could potentially add actionable insights to existing research methods. For example, a moment-by-moment read-out of neural similarity during a long video will be valuable for content creators to locate quickly where editing is warranted. While cost remains a barrier for many marketing practitioners who want to employ neuroimaging methods, there are two reasons to be optimistic. First, the cost for acquiring and operating equipment necessary for many neuromarketing methods, such as eye-tracking or mobile EEG, is generally trending down over the years. Second, as the findings in Chapter 3 and other past studies have shown, it is possible to extract neural representations that are common across individuals. It is foreseeable in future that a neural template database can be established as neuroimaging data accumulate, resulting in pre-built neural classifiers with minimal calibration needed and thereby making mental content decoding more time and resource efficient.

5.3 Limitations and future research directions

Notwithstanding the contributions of these studies, several limitations should be noted here, which also shed light on future research directions.

The neural representations investigated throughout this dissertation are limited to spatiotemporal BOLD signal patterns. There are other ways to extract distributed patterns, such as functional connectivity, i.e., temporal coherence in spatially remote brain regions (Friston, 2011). For example, functional connectivity analysis of reward processing revealed a topographically distinct network when compared to the previous standard fMRI analysis (Camara, Rodriguez-Fornells, & Münte, 2008). Moreover, using whole-brain connectivity patterns observed during video-watching, researchers have been able to identify the video segments that evoked such patterns (Richiardi, Eryilmaz, Schwartz, Vuilleumier, & Van De Ville, 2011). Future studies should therefore explore the role of functional connectivity patterns in the encoding of consumer experience, and whether it can provide additional information than spatiotemporal patterns alone.

In our studies where pattern classifications were conducted (Chapter 2 and 3), predictive accuracy rates (60-70% in a two-category classification; ~40% in a four-category classification) tended to be lower compared to studies involving perceptual stimuli (Haxby et al., 2001; Kay et al., 2008). This is probably due to both the noisy nature of fMRI recordings, and also inherent within- and between-subject variability in higher-order mental processes. While neuroscientists are continuously developing ways to increase signal-to-noise ratio in neuroimaging data, the ceiling for neuro-classification accuracy may eventually still be too low for practical applications. On the other hand, correlations between neural measures and out-of-sample variables (Chapter 2 and 4) typically ranged between .5 – .7, which means neural measures could explain about 25–50% of the variance in target outcome measures. While not excessively low, performance at the current level suggests there remains

significant room for refinement in both measurement and analysis before ‘neuroforecasting’ becomes a commercially viable tool.

More conceptually speaking, while the studies in this dissertation illustrate the marketing implications of group similarity in brain responses, it is not clear to what extent the similar-is-good observation is generalizable. As suggested in Chapter 4, for cultural products that are supposed to provoke discussion and mental stimulation, such as documentaries or poeties, we should expect dissimilar neural responses across individuals as the desirable outcome. Moreover, neural dissimilarity may prove to be a useful tool for market segmentation (Wedel & Kamakura, 2012). Future studies should investigate this potential interaction effect of product or audience characteristics on neural similarity.

5.4 Concluding remark

The mission to better understand of the mind of consumers by neuroimaging methods is still in its early stage. While being mindful of its technical and ethical challenges (Stanton, Sinnott-Armstrong, & Huettel, 2017), it is the author’s belief that consumer neuroscience will continue to inform marketing research through innovations and creativity. This dissertation represents one such endeavor in this continuing journey.

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Summary

Understanding consumer experience – what consumers think about brands, how they feel about services, whether they like certain products – is crucial to marketing practitioners. ‘Neuromarketing’, as the application of neuroscience in marketing research is called, has generated excitement with the promise of understanding consumers’ mind by probing their brains directly. Recent advances in neuroimaging analysis leverage machine learning and pattern classification techniques to uncover stable spatial or temporal representations from neuroimaging data that can be associated with thoughts and feelings. As such, the so-called multivariate pattern analysis (MVPA) of functional magnetic resonance imaging (fMRI) recordings offers researchers and practitioners an exciting opportunity to ‘decode’ the consumer’s mind.

In this dissertation, I explore and analyze neural representations (multi-voxel blood oxygenation level dependent signal patterns) of consumer experience with MVPA techniques. The potential advantage of this approach is that it allows researchers to examine (a) nonverbal experience (e.g., visual associations of brands) and (b) ephemeral experience (e.g., emotional responses during video watching) of consumers.

In Chapter 2, I show how neuroimaging can be used to ‘decode’ consumer knowledge, specifically the visual image consumers associate with a brand. 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, individual neural profiles of brand image can be generated. These neural profiles track the participant’s

own self-reported brand perception, and in aggregate, offer a measure of brand image strength. Overall, the study demonstrates the potential of analyzing representational similarity of neuroimaging data to study multi-sensory, nonverbal consumer knowledge and experience.

In Chapter 3, I explore the feasibility of using neural representations from brief, stable affective episodes (viewing affective pictures) to decode extended, dynamic affective sequences in a naturalistic experience (watching movie-trailers). Using this approach, I found that decoded valence and arousal responses during video watching tracked self-reported valence and arousal; in addition, the decoded affect time series could be used to identify movie-trailers, suggesting that they represented the common experience across participants. This study provides further support for the possibility of using pre-trained neural classifiers to decode dynamic affective responses during a naturalistic experience.

In Chapter 4, I investigate if representation-based analysis improves market outcome prediction. Specifically, I draw inspiration from the latest advancements in inter-subject correlation research (i.e., the consistency of neural responses across individuals). In the study, spatiotemporal neural similarity at temporal lobe and cerebellum during video watching predicts out-of-sample preference and recall of videos. Overall, this study suggests that neural similarity at temporal lobe and cerebellum – traditionally associated with sensory integration and emotional processing – reflect the level of engagement with video stimuli.

Three observations can be made from the studies in this dissertation. First, we show that at least part of the consumer experience is encoded in spatiotemporal neural patterns. Based on various pattern analysis techniques, these neural representations can offer rich, multi-dimensional knowledge about consumer experience. Second, by adopting a template-based decoding approach, we can infer mental content based on spatiotemporal activation patterns in the brain. This series of studies hopefully lay the groundwork for

the expansion of consumer neuroscience from resolving ‘how consumers use their mind’, to focusing on ‘what consumers have in mind’. Third, this dissertation provides evidence that consumer response consistency at the neural level indicates the quality of consumer experience, and by extension that of marketing actions, opening up a new line of research.

The mission to better understand the mind of consumers by neuroimaging methods is still in its early stage. While being mindful of its technical and ethical challenges, it is the author’s belief that consumer neuroscience will continue to inform marketing research through innovations and creativity. This dissertation represents one such endeavor in this continuing journey.

Samenvatting (Summary in Dutch)

Het meten en begrijpen van hoe consumenten merken, producten en diensten ervaren is essentieel voor marketeers. De toepassing van methoden en inzichten uit de neurowetenschappen op het gebied van marketing, oftewel neuromarketing, kan bijdragen om gedachten en ervaringen van consumenten beter te kunnen doorgronden door direct hun hersenen te onderzoeken. In recente ontwikkelingen in neuroimaging wordt gebruik gemaakt van geavanceerde statistische technieken om hersenactiviteit te koppelen aan gedachten en gevoelens. In dit proefschrift onderzoek ik hoe multivariate patroonherkenning (MVPA), toegepast op functionele MRI (fMRI) data, onderzoekers en marketeers de mogelijkheid kan geven om het brein van consumenten te doorgronden. De voordelen van deze aanpak zijn dat het onderzoekers in staat stelt om ook non-verbale ervaringen (bijv. visuele merk associaties) of kortstondige ervaringen (bijv. emotionele gevoelens) te onderzoeken.

In hoofdstuk 2 van dit proefschrift onderzoek ik hoe we *neuroimaging* (hersenscans door middel van fMRI) kunnen gebruiken om consumentenkennis in kaart te brengen met betrekking tot merkassociaties. Hierbij richt ik mij specifiek op het beeld dat consumenten van verschillende merken hebben. We genereren *neural profiles* ('profielen van hersenactiviteit') van iedere proefpersoon door hersenactiviteit van relevante stimuli (in ons geval, foto's van sociale situaties waarin een merk gebruikt kan worden) te meten. Vervolgens vergelijken we deze *neural profiles* met de hersenactiviteit tijdens het actief visualiseren van merkassociaties. De neurale bevindingen

zijn in lijn met de zelfgerapporteerde merkperceptie van de proefpersonen, en welke merken het beste kunnen samenwerken (co-branding suitability). Tevens kunnen we op basis van de mate waarin de neurale activiteit overeenkomt tussen proefpersonen, de sterkte van een merk bepalen. Dit onderzoek laat het potentieel zien van het analyseren van overeenkomsten in hersenactiviteit en stelt ons in staat om non-verbale consumentenkennis en ervaring te meten zonder consumenten vragen te stellen over hun merkbeeld.

In hoofdstuk 3 onderzoek ik in hoeverre neural profiles van kortdurende stimuli (foto's die een emotie oproepen) iets zeggen over hoe dynamische en langerdurende stimuli emotioneel worden ervaren (in ons geval, filmtrailers). Met onze aanpak vind ik dat de voorspelde emoties op basis van de hersenactiviteit van de proefpersonen dicht bij de zelf-gerapporteerde emoties liggen. Dit geldt zowel voor *valence* (positief versus negatief gevoel) als voor *arousal* (intensiteit van de emotionele reactie). Bovendien zijn de voorspelde emotionele variaties onderscheidend genoeg om de verschillende trailers te identificeren, wat suggereert dat er een gezamenlijke ervaring is tussen de proefpersonen. Dit onderzoek draagt bij aan het idee dat vooraf getrainde *neural classifiers* (patronen van hersenactiviteit) gebruikt kunnen worden om emoties en gevoelens af te leiden uit de hersenactiviteit gemeten bij andere stimuli.

In hoofdstuk 4 onderzoek ik of een zogenaamde *representation-based* analyse kan helpen om de kwaliteit van voorspellingen te verbeteren. In het bijzonder gebruik ik de laatste ontwikkelingen op het gebied van inter-subject correlatie onderzoek (dat is, mate van overeenkomst in hersenactiviteit tussen individuen). Overeenkomsten in de hersenactiviteit in de temporaalkwab en het cerebellum helpen bij het voorspellen van *preference* (voorkeur) en *recall* (mate van herinnering) van de proefpersonen. Omdat deze hersengebieden traditioneel worden geassocieerd met zintuigelijke verwerking en het verwerken van emoties, zeggen overeenkomsten in activiteit in deze gebieden ons waarschijnlijk iets over het niveau van betrokkenheid van de persoon met de video.

Dit proefschrift bevat drie hoofdconclusies. Ten eerste laat ik zien dat een deel van de consumentenervaring te relateren is aan patronen in hersenactiviteit (zowel over de tijd als de locatie). Deze *neural profiles* geven een waardevolle inkijk in de verschillende dimensies van de consumentenervaring. Ten tweede, door met behulp van statistische methoden een profiel van hersenactiviteit op te stellen, kunnen we ‘gedachten lezen’. Deze serie onderzoeken legt hopelijk een basis om de consumentenneurowetenschap naar een hoger niveau te tillen, van het uitzoeken ‘van hoe consumenten hun hersenen gebruiken’ naar ‘wat consumenten denken’. Tenslotte toont dit proefschrift aan dat een hogere consistentie in hersenactiviteit een indicatie is voor een betere consumentenervaring. Omdat de beslissingen van marketeers direct invloed hebben op de consumentenervaring, openen deze nieuwe technieken en inzichten de deur voor een volledig nieuw onderzoeksgebied.

De missie om de gedachten van consumenten beter te begrijpen met behulp van *neuroimaging* bevindt zich nog in een vroeg stadium. Ondanks alle technische en ethische uitdagingen, ben ik van mening dat de consumentenneurowetenschap zal blijven bijdragen aan marketingonderzoek. Dit proefschrift vormt slechts het begin van deze avontuurlijke reis.

研究撮要 (Summary in Chinese)

了解消費者體驗——對品牌的印像、對服務的感覺、對產品的評價——對於市場營銷從業者相當重要。將腦神經科學應用於市場營銷研究，即所謂「腦神經市場營銷學」(neuromarketing)，透過直接測量腦部從而了解消費者，此方法有令人期待的潛力。隨着腦顯影分析不斷演進，近年發展至利用機器學習和模式識別技巧，於腦部顯影數據中找尋代表情感和思緒的立體或時序訊息表徵。以功能性磁力共振顯影 (functional magnetic resonance imaging, fMRI) 為本的多體素模式分析 (multivariate pattern analysis, MVPA)，理論上可以讓科研或營銷人士解讀消費者腦中思想。

本論文嘗試以 MVPA 技巧，探索和分析消費者的「腦訊息表徵」（即由多體素血氧水平訊息組成的模式）。此種方式的好處，在於可以研究消費者的非語言體驗（如品牌形象）和實時體驗（如觀看視像）。

論文第二章探討如何使用腦顯影數據「解讀」消費者的認知；具體而言，即是消費者對於各品牌形象的視覺聯想。透過撮取消費者觀看各式視覺模版（描繪不同社交場合的圖片）時的腦部反應，並將之對比他們在腦中重塑品牌形象畫面的腦部反應，可以得出個人品牌形象認

知的腦反應剖析。這些腦反應剖析，符合消費者自己對品牌認知的表述，通過總體分析亦可以反映品牌形像的強弱。總括而言，此項研究示範了如何透過比較腦訊息表徵，研究消費者多感官、非語言的內在體驗和認知。

論文第三章探索於觀看圖片誘導情緒時撮取的靜態腦訊息表徵，能否用於解讀動態情緒自然反應（如觀賞電影預告片）。透過此方法解讀實驗參加者觀看錄像時的腦部反應，所得出的情緒正負和強度，符合參加者觀賞後的自我評價。除此之外，腦部反應分析得出的情緒正負和強度時序數據，可以反過來識別參加者正在觀賞哪齣電影，反映解讀器能辨析參加者的共同體驗。此項研究展示如何透過預先訓練的腦部情緒解讀器，分析消費者於動態體驗時的情緒自然反應。

論文第四章研究腦訊息表徵分析能否改良市場預測。研究建基於近年興起的群體腦反應相關性研究（即是指不同人的腦部反應是否一致）。此項研究發現，觀看錄像時顳葉和小腦時空訊息表徵的群體相似性，可以預測樣本外錄像偏好和記憶率。總括而言，研究結果顯示，負責綜合感官和處理情緒的顳葉和小腦，其群體反應相似性可以反映錄像令人投入的程度。

綜合而言，本論文研究有三大結論。首先，腦部反應的立體及時序訊息表徵，可以反映消費者的體驗。透過模式分析技術解讀腦部訊息表徵，研究人員可以多向度分析消費者體驗。第二，利用模版為本的解讀方式，我們可以根據腦部反應推敲出消費者的思緒和情感。此方法為腦神經市場營銷學打開新的探索之門，由研究消費者腦部運作原理，擴展至解讀消費者思緒。第三，本論文顯示出群體腦部反應相似

性，可以反映消費者體驗的質素好壞，憑此亦可以測度市場營銷的成效，為市場營銷學打開新的研究領域。

利用腦顯影技術測量消費者心理的研究，仍然在於起步階段。論文作者相信，儘管此方法仍有不少技術上和倫理上的挑戰，透過不斷創新，腦神經科學應用於市場營銷研究，將會帶來種種成果。本論文正是推進此研究領域的其中一例。

About the Author



Hang-Yee Chan was born in Hong Kong, China. He received his Bachelor's degree in Cognitive Science from the University of Hong Kong (first class honors). Afterwards, he obtained his first Master's degree in Human and Environmental Studies at Kyoto University, Kyoto, Japan; and his second Master's degree in Cognitive Science at École Normale Supérieure, Paris, France. In 2014, he started his PhD research in Marketing at the Erasmus Research Institute in Management, specializing in consumer neuroscience. He was a visiting research scholar at Stanford University (August to December 2017) and University of Pennsylvania (September 2018).

His research interest lies in the use of neuroimaging data to uncover consumer's thoughts and feelings. His work has been published in both top marketing and neuroscience journals, such as *Journal of Marketing Research* and *NeuroImage*. His work on neural profiling of brand image has won him the ERIM Top Article Award 2019. He also presented at major international conferences, including the Annual Conference of the Society for Neuroeconomics and the European Association of Consumer Research Conference.

In September 2019, he started working as a postdoctoral researcher at the University of Amsterdam.

Portfolio

A. Publications

Chan, H.-Y., Boksem, M. A. S., & Smidts, A. (2018). Neural Profiling of Brands: Mapping Brand Image in Consumers' Brains with Visual Templates. *Journal of Marketing Research*, 55(4), 600–615. (Winner of ERIM Top Article Award 2019)

Chan, H.-Y., Smidts, A., Schoots, V. C., Dietvorst, R. C., & Boksem, M. A. S. (2019). Neural similarity at temporal lobe and cerebellum predicts out-of-sample preference and recall for video stimuli. *NeuroImage*, 197, 391–401.

Chan, H.-Y., Smidts, A., Schoots, V. C., Sanfey, A. G., Boksem, M. A., Smidts, A. (in press). Decoding dynamic affective responses to naturalistic videos with shared neural patterns. *NeuroImage*.

B. Working papers

Chan, H.-Y., Smidts, A., Dietvorst, R. C., Boksem, M. A., Smidts, A. "Temporal change in correlation between neural signal and preference." Manuscript in prep.

Chan, H.-Y., Gunadi, M., Schley, D. "Dynamic representation of probabilistic forecasts influences trust and betting behavior." Manuscript in prep.

Chan, H.-Y., Scholz, C., Falk, E. “Neural correlates of individual differences in information sharing.” Manuscript in prep.

Genevsky, A., Chan, H.-Y., Knutson, B., Huber, J. “Neural signals during evaluation of multi-feature products: A comparison with conjoint analysis.” Data analysis in progress.

C. Research visits

- 2018 Annenberg School for Communication, University of Pennsylvania (Emily Falk)
- 2017 Department of Psychology, Stanford University (Brian Knutson)

D. Conference presentations

- 2018 European Association of Consumer Research Conference, Ghent
Annual Interdisciplinary Symposium on Decision Neuroscience (ISDN), Ann Arbor, MI
- 2017 Annual Conference of the Society for Neuroeconomics, Toronto
- 2016 Consumer Neuroscience Symposium, Berlin
Annual Conference of the Society for Neuroeconomics, Berlin
Annual Interdisciplinary Symposium on Decision Neuroscience (ISDN), Philadelphia
- 2015 Annual Interdisciplinary Symposium on Decision Neuroscience (ISDN), Cambridge
Consumer Neuroscience Symposium, Miami
Annual Conference of the Society for Neuroeconomics, Miami

E. Teaching experience

Master Thesis Co-readership (2017-19)

Research Training and Bachelor Thesis (2016-19)

Neuromarketing (2015-19)

Neuroeconomics (2016-18)

F. Professional and administrative service

Reviewer, *Journal of Cognitive Neuroscience*

Reviewer, *Journal of Consumer Psychology*

Coordinator of cloud computing for neuromarketing research

G. Selected coursework

Workshops

- Introduction to High-Performance Machine Learning, *SURFsara*
- Data Intensive Computing with Spark and Hadoop, *University of Amsterdam*
- Shanghai Neuroeconomics Summer School, *NYU Shanghai*
- Eye-Tracking for Visual Marketing Workshop, *HEC Paris*
- PyMVPA Workshop, *Giessen University*

PhD Courses

- Behavioural Decision Theory
- Machine Learning
- Applied Econometrics
- Micro Economics
- Advanced Statistical Methods

H. Scholarships and awards

- ERIM Top Article Award (2019)
- ERIM Talent Placement Program, €30,000
- Erasmus Trustfonds, €700
- Alexandre Yersin Excellence Scholarship, €12,000
- Monbukagakusho (MEXT) Scholarship, ¥5,600,000

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Kerkkamp, R.B.O., *Optimisation Models for Supply Chain Coordination under Information Asymmetry*, Promotors: Prof. A.P.M. Wagelmans & Dr. W. van den Heuvel, EPS-2018-462-LIS, <https://repub.eur.nl/pub/109770>

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Understanding consumer experience – what consumers think about brands, how they feel about services, whether they like certain products – is crucial to marketing practitioners. ‘Neuromarketing’, as the application of neuroscience in marketing research is called, has generated excitement with the promise of understanding consumers’ minds by probing their brains directly. Recent advances in neuroimaging analysis leverage machine learning and pattern classification techniques to uncover patterns from neuroimaging data that can be associated with thoughts and feelings. In this dissertation, I measure brain responses of consumers by functional magnetic resonance imaging (fMRI) in order to ‘decode’ their mind. In three different studies, I have demonstrated how different aspects of consumer experience can be studied with fMRI recordings. First, I study how consumers think about brand image by comparing their brain responses during passive viewing of visual templates (photos depicting various social scenarios) to those during active visualizing of a brand’s image. Second, I use brain responses during viewing of affective pictures to decode emotional responses during watching of movie-trailers. Lastly, I examine whether marketing videos that evoke similar brain responses among consumers turn out performing better in the market. These three studies show how analysis of brain responses uncovers nonverbal and ephemeral experiences of consumers. While mindful of the technical and ethical challenges, this dissertation hopefully lays the groundwork for the expansion of consumer neuroscience from resolving ‘how consumers use their mind’ to focusing on ‘what consumers have in mind’.

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