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Mapping Consumer Cognition and Emotions: A Neuroscientific Approach

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MAPPING CONSUMER COGNITION AND EMOTIONS:
A NEUROSCIENTIFIC APPROACH

A Dissertation

by

DONGJUN REW

Submitted to the Graduate College of
The University of Texas Rio Grande Valley
In partial fulfillment of the requirements for the degree of

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Major Subject: Business Administration

MAPPING CONSUMER COGNITION AND EMOTIONS:
A NEUROSCIENTIFIC APPROACH

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July 2019

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ABSTRACT

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Although the rival theories for consumer decision making process, cognitive perspective and experiential perspective, have successfully contributed to the marketing discipline, there is an alternative point of view that cognition and emotions work together for a decision or even a behavior. However, the methodological limitation has been a big hurdle that interrupts insightfulness and fruitfulness of marketing research, especially in consumer research. This study thus aims to develop a brain map and functional connectivity of consumer decision making and emotions to show physiological and neurological evidence that emotional behaviors and cognitive behaviors are associated when consumers decide a behavior by analyzing functional magnetic resonance image (fMRI) data. Activation likelihood estimation (ALE) meta-analysis and network analysis (correlation-based machine learning algorithm) are employed and performed. Findings of two individual studies show the neurological evidence that neural regions for emotional (fear, sadness, happiness, disgust, surprise, and anger as a proxy of emotional behaviors) and consumer decision making are interactive. The research successfully performed a consumer brain connectivity for consumer decision making and emotions based on the network theory. With the findings, this research would have contributions to the marketing discipline by piling up neurological, physiological, and behavioral knowledge to better understand consumer behaviors.

DEDICATION

I dedicate this dissertation to my family. It would be impossible to complete my doctoral program without their uncountable supports and devotion. Especially, the love of my wife and her praying made me confident and strong enough to complete this long marathon. I also would like to thank my parents who are still praying for me.

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TABLE OF CONTENTS

	Page
ABSTRACT	iii
DEDICATION	iv
ACKNOWLEDGMENTS	v
TABLE OF CONTENTS	vi
LIST OF TABLES	viii
LIST OF FIGURES	ix
CHAPTER I. INTRODUCTION	1
CHAPTER II. LITERATURE REVIEW AND RESEARCH FRAMEWORK.....	14
A Short History of Consumer Neuroscience.....	14
Consumer Decision-Making	18
Emotions	22
Categories of emotional behaviors	25
Functional Connectivity	31
Network theory	32
The Association between Decision Making and Emotions and Its Connectivity.....	34

CHAPTER III. METHODOLOGY.....	37
Systematic Review.....	37
Literature search	39
Study selection	39
Data collection process	41
Activation Likelihood Estimation (ALE) Meta-Analysis	42
Brain Connectivity (Study 2)	44
CHAPTER IV. ANALYSIS AND RESULTS.....	48
Pilot Study 1	48
Pilot Study 2	53
Study 1 (Association between Emotions and Consumer Decision Making)	57
Study 2 (Brain Functional Connectivity)	66
CHPATER V. CONCLUSION AND DISCUSSION	82
Managerial Implication.....	84
Limitations and Future Research.....	85
REFERENCES.....	87
BIOGRAPHICAL SKETCH	112

LIST OF TABLES

	Page
Table 1: Projects/Databases Related to the Human Brain Study.....	8
Table 2: Research Structure	11
Table 3: Literature of Decision Neuroscience	16
Table 4: Consumer Research on Brain Regions Activated for Consumer Decision Making	20
Table 5: Methods for Study 1 and Study 2	47
Table 6: fMRI Studies Included in the Meta-analysis	50
Table 7: ALE Activation Clusters Associated with Emotion (Happiness)	51
Table 8: ALE Activation Clusters Associated with Cognition (Language)	52
Table 9: Brain Regions for Emotional Behaviors Identified with Colors	54
Table 10: fMRI Studies of Cognitive Behaviors (Language and Working Memory)	58
Table 11: ALE Activation Clusters Associated with Consumer Decision-Making	60
Table 12: fMRI Studies of Emotional Behaviors	61
Table 13: ALE Activation Clusters Associated with Emotions	63
Table 14: The Results of Contrast Analysis in ALE Meta-analysis	80
Table 15: Central Nodes of Each Behavior	81

LIST OF FIGURES

	Page
Figure 1: Numbers of Published Articles in Neuromarketing and Neuroscience.....	4
Figure 2: Research Framework	36
Figure 3: Summary of Literature Search Adapted from PRISMA.....	40
Figure 4: Brain Regions for Each Behavior in PS1	53
Figure 5: Screen Captures of 3D Draft Brain Mapping (Emotions).....	56
Figure 6: Activated Brain Regions for Emotional and Consumer Decision-Making.....	66
Figure 7: Examples of an fMRI Image	69
Figure 8: The Neural Connectivity of Emotions (in-degree)	72
Figure 9: The Neural Connectivity of Emotions (out-degree).....	74
Figure 10: The Neural Connectivity of Cognition (in-degree)	76
Figure 11: The Neural Connectivity of Cognition (out-degree).....	78

CHAPTER I

INTRODUCTION

“A journey of a thousand miles must begin with the first step” – attributed to Lao-Tzu

This proverb means that everything starts with a small thing. In other words, attaining a level of achievement requires an initial process that lays the foundation for the achievement or goal. In this regard, consumer research has been continuously developed to include different perspectives of other disciplines such as psychology and economics (Moorthy, Ratchford, & Talukdar, 1997). Lowenstein (2001) considers this development in consumer research as creative destruction. Thus, to take another major step forward in consumer research, researchers must break the boundaries of research including research subjects, area, topics, and especially research methods. Through these breaks, consumer researchers are able to develop a research model that helps to parsimoniously explain and understand a phenomenon that is interlaced with complicated social and behavioral relationships in a market, such as connections of neurons in the brain.

This creative destruction in consumer research has attempted to expand the research territory, such as in the new field of consumer neuroscience. Consumer neuroscience applies tools and theories from neuroscience to better understand decision-making and related processes (Plassmann, Venkatraman, Huettel, & Yoon, 2015). Based on the knowledge of neuroscience proposing that each individual has different neural correlates from others (Frith & Frith, 2001;

Gallagher & Frith, 2003), consumer research can yield fruitful findings and meaningful insights to deeply understand consumer behaviors.

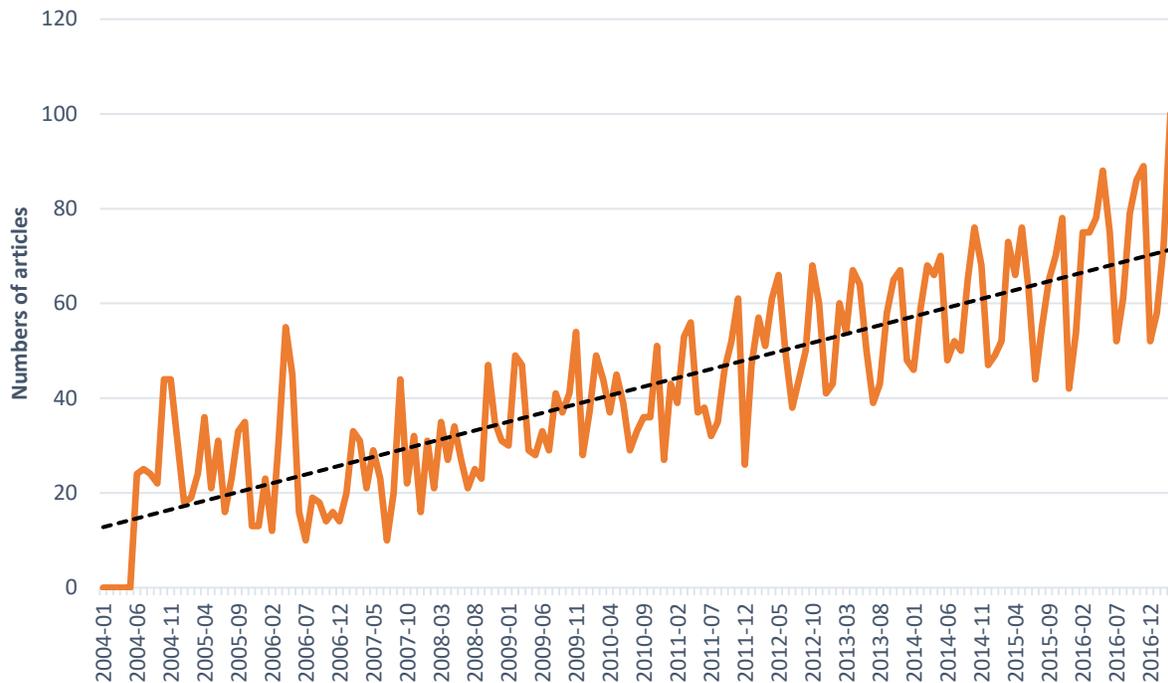
In the area of consumer research, different research methods have been used to investigate consumer behavior, such as electroencephalography (EEG), functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), positron emission tomography (PET), single neuron recording, multineuron recording, lesion studies, transcranial direct current stimulation (tDCS), diffusion tensor imaging (DTI), and transcranial magnetic stimulation (TMSW) (Wang & Minor, 2008). In particular, functional Magnetic Resonance Imaging (hereafter fMRI) has been a popularly employed research method that has enhanced consumer research more meaningfully and fruitfully. This technique enables consumer researchers to more accurately understand and explain patterns of consumer behaviors by examining a specific activated region in the brain. For instance, Yoon and her colleagues (2006) used fMRI techniques to attempt to investigate whether there is a compatible process between semantic judgments about products and consumers. Rampl, Optiz, Welp, and Kenning (2016) employed fMRI to find brain activations for emotions when consumers choose a brand through comparing two different types of brands, employee-preferred brands, and consumer-preferred brands.

fMRI is a relatively newer technique than traditional methods, such as survey and interview. The reason for the heightened interest in using neuroscientific methods in consumer research is that neuroscientific methods are more reliable than traditional ways that are potentially more susceptible to experimenter bias or demand effects (Shaw & Bagozzi, 2018). fMRI aims to investigate functional specificity at high resolution in humans (Oop de Beeck, Haushofer, & Kanwisher, 2008). This brain imaging technology enables researchers to expand the boundary of consumer research by drawing a detailed picture of the functional organization

of the human brain (Poldrack, 2006). In summary, research using fMRI has vastly increased and diversely expanded the scope of the research in consumer and cognitive science from finding a specific brain region activated by an external and internal stimulus to testing individuals' psychological response to ads, commercials, and other stimuli.

Ramsøy (2014) points out the relevance of this consumer research trend within the domains of neuromarketing and neuroscience. The research trend is illustrated in Figure 1, which was created from data from Google Trends with the search keywords neuromarketing and consumer neuroscience. The graph shows that since 2004, when neurological research methods such as EEG, fMRI, DTI, and PET were introduced to the marketing discipline, using the methods in consumer research known as consumer neuroscience and neuromarketing has progressively increased (Ramsøy, 2014). Figure 1 presents the pattern of increasing interest in neuroscientific research by showing that the number of published articles including consumer neuroscience and neuropsychology has considerably increased every year since 2004. The black dotted line in the middle of the data movement shows the positive association between the y variable (number of published articles) and the x variable (year).

Figure 1. Numbers of Published Articles in Neuromarketing and Neuroscience



Another reason for using neuroscientific methods in consumer research is to map the consumer's brain based on the mechanism of brain activation or response to an internal or external stimulus. This technique allows researchers to more clearly and anatomically understand consumer behaviors, such as decision-making, consumer preference and choice, and consumer responses to marketing programs including price, place, promotion and product (4 Ps). This type of research can only thus be done using neuroscientific methods. For instance, fMRI helps researchers not only investigate a specific activated region for a specific behavior such as preference, attitude, or justification but also draw a map of the brain connections with the specific regions. This metabolic pathway is referred to as connectivity, which means the networks in the human brain (Seung, 2013; Sporns, 2011, 2013; Sporns, Tononi, & Kotter, 2005). Recent advances in neuroimaging enable researchers to examine human brain connectivity systemically (Sporns, 2012). In other words, a small connection or relationship between a neural region and a certain behavior makes a big picture of brain connectivity.

Describing the big picture is especially important because it helps consumer researchers to develop a parsimonious model to explain and understand why and how consumers are behaving and making a decision, behaviorally and physiologically.

Research gap and research questions

Historically, in the marketing discipline, especially in consumer research, there have been three theories or models proffered to explain the consumer decision-making process: the cognitive perspective (Bettman, 1979; Cacioppo, Petty, Kao, & Rodriguez, 1986), the experiential perspective (Holbrook & Hirschman, 1982), and the environmental perspective (Donavan, Minor, & Mowen, 2016; Duncan & Humphreys, 1989).

The cognition-oriented approach argues that when consumers decide what they will consume, they focus on cognitive behaviors including judgment and memory. This leads to a 5-step model: recognize shortages, search for alternatives to fill the shortages, compare searched alternatives, choose one of the alternatives, and evaluate the choice (Bettman, Luce, & Payne, 1998). This process model of consumer decision-making is useful to understand how consumers decide what they are willing to purchase through a series of intellectual steps.

In contrast, the experiential perspective insists that consumers are not only thinkers or rational decision makers, but also feelers or irrational decision makers. Thus, this point of view weightily considers consumer's feelings as a core of consumer decision-making. This model is helpful to understand why consumers consume impulsively and explains the pattern of hedonic consumption.

The last approach considers environments surrounding consumers as influences that affect consumer decision-making, such as other's opinions, information about a product/service,

and mood or design of places such as scent or colors in restaurants and stores. In other words, consumers' bottom-up attention is driven by environmental cues. This point of view attempts to find factors that affect decision-making from outside the body, while the previous two models look for the factors inside the body.

On the basis of the three decision-making models, two mainly discussed factors affecting or consisting of decision-making have been identified and centered in consumer research: cognition and emotions (Shaw & Bagozzi, 2018). The argument about whether cognition or emotion is more important for individuals to decide their behaviors (e.g., attitudes, satisfaction, purchasing and engagement) has also existed in the neuroscience discipline (Dolan, 2002; Pessoa, 2008). Thus, it would be relevant in the marketing discipline to discuss this argument from the neuroscientific point of view because consumer research using neuroscientific methods can develop and provide a meaningful perspective or model to parsimoniously understand and explain consumer behaviors, especially consumer decision-making. As of now, there have been many studies on consumer decision-making process in the marketing discipline. While consumer decision-making is an important physiological parameter, there have been few studies in the marketing discipline looking for and showing neurological evidence that specific brain areas for the two factors are activated when individuals make a decision. The reason for the lack of physiological and behavioral knowledge about consumer decision-making is that most consumer research has been conducted using traditional research methods including survey and interview (Shaw & Bagozzi, 2018). This lack of study makes it difficult to find empirical evidence that supports previous theoretical arguments that emotions are important when consumers make a decision and to contribute to the knowledge about consumer behaviors.

This research will employ fMRI datasets publicly released by the Human Connectome Project (hereafter HCP). HCP (hereafter HCP1) is sponsored by the United States National Institute of Health (NIH) project consortium and led by three universities: Washington University, the University of Minnesota, and Oxford University. The consortium has undertaken systematic research to map macroscopic human brain circuits and their relationship to behavior in a large population of healthy adults (Van Essen et al., 2013). This project has provided human brain images to increase the probability of curing brain disease and contribute to understanding the connections within the human brain. The project currently operates the Connectome Coordination Facility (CCF) that houses and distributes public research data, especially in the form of fMRI. With regard to this connectome project, there are different types of government-granted connectome projects: “OpenNEURO” by Dr. Russel Poldrack and his laboratory at Stanford University, which shares neuroscientific research and results with researchers, and the Human Connectome Project by two US medical schools, the University of South Carolina Medical School and Harvard Medical School (hereafter HCP2).

The difference between HCP1 and HCP2 is the type of study they are conducting. HCP2 is centered around a consortium of researchers at the two US medical schools and aims to provide an unparalleled compilation of neural data to deeply understand the human brain by mapping the structural neural connection (www.humanconnectomeproject.org). HCP1 is a consortium among three universities (i.e., Washington University at St. Louis, University of Minnesota, and Oxford University) that aims to provide medical information about brain diseases and to understand the human brain by researching the connections of brain functions (www.humanconnectome.org). Although both government-funded projects provide public brain image data, the datasets from CCF operated by HCP1 will be used for this study because they

provide datasets of functional brain images that show brain activity for specific behaviors. Another reason for using HCP1 datasets is that they provide clearer sets of data after preprocessing a set of raw brain images from fMRI. They also share general (or resting) brain images of over 1200 healthy adults to the public, while HCP2 provides limited brain images designed for specific studies rather than resting fMRI data. Table 1 displays the data types and purposes for each project.

Table 1. Projects/Databases Related to the Human Brain Study

Project	Consortium	Fund	Purpose	Data
Human Connectome Project (HCP1) operating CCF	Washington University at St. Louis, the University of Minnesota, and Oxford University	NIH	Distributing public research data that focus on the connections of human brains Understanding of human brain diseases and human behaviors	fMRI (3T/7T diffusion data, 3T retest data) Available for 1,200 subjects
Human Connectome Project (HCP2)	The University of South Carolina and Harvard Medical School	NIH	Mapping the human brain by diffusion spectrum imaging (DSI) for white matter fiber pathways and functional correlations analysis	fMRI (3T diffusion data) Available for 40,444 subjects from 116 studies (only 40 subjects diffusion data)
OpenNEURO	Stanford University	NSF NIH	Sharing raw magnetic resonance imaging (MRI) datasets to understand human brain structures and functions	MRI, EEG, and fMRI Available 3,372 subjects

Notes: NIH – National Institute of Health, NSF – National Science Foundation

There has been a limited amount of research using the large datasets on connectivity to investigate the possibility of a relationship among brain regions activated for behaviors. Smith et al. (2015) investigated the relationship between individual subjects' functional connectomes and 280 behavioral and demographic measures in a single holistic multivariate analysis relating imaging to non-imaging data from 461 subjects in the HCP1. Finn et al. (2015) and Kruschwitz, Waller, Daedelow, Walter, and Veer (2018) attempted to find the association between general intelligence and global functional efficiency using the large dataset (more than 1200 subjects)

provided by HCP1. Researchers in the neuroscience discipline have attempted to find the connectivity among brain functions and the regions and to test the generalizability, reliability, and validity of data from HCP1 in terms of examining the usability of the dataset in a neuroscientific study. However, there is only a limited number of studies on brain mapping to explain and understand the brain's functional efficiency for decision-making in consumer research (Geissmann et al., 2018; Smith et al., 2015; Yoo et al., 2018).

To reduce this knowledge gap, this study will conduct a systematic literature review and meta-analyses to explore the interaction between cognition and emotions by finding the common neural areas activated for emotions and decision-making. Then, it will draw a functional connectivity (map) of relationships among the neural areas of each of the two main models (cognitive perspective vs. experiential perspective) to neurologically and physiologically understand the consumer decision-making process and support an alternative model showing the neural interaction between emotions and consumer decision-making. To increase physiological and behavioral knowledge of consumer behaviors, this study will look for consumer decision-making, its neural activated region, and neural interactions with consumer emotions guided by the following research questions:

- 1) Which decision-making perspective is better to explain consumer decision-making?
- 2) What regions of the brain are activated in emotions and consumer decision-making?
- 3) If there are fixed regions for each of emotions and decision-making and working together in the brain, how physiologically are neural areas for emotions and decision-making connected in the brain?

Research purpose

To answer these questions, this study will attempt to find the interaction between consumer decision-making and emotions through activation likelihood estimation (ALE) meta-analysis indicating the largest volumes (detected by blood oxygenation level dependent, or BOLD) associated with a certain behavior. There are different types of behaviors in the cognitive and emotional realms. Cognitive behaviors include memory, language, problem-solving, attention, visual imagery, pattern recognition, and decision-making (Reed, 2013), while emotional behaviors include fear, disgust, happiness, sadness, surprise, and anger (Gasquoine, 2016). This study only focuses on decision-making as a cognitive behavior and all the six feelings as emotional behaviors to explore the interaction between decision-making and emotions by finding activated neural areas for both types of behaviors. For the analysis, the HCP1 brain image datasets including the brain images of over 1200 healthy adults were examined to find a systematic pattern of human behaviors through analyzing and understanding brain images showing specific brain region activated for stimuli (Poldrack & Gorgolewski, 2014).

In addition to ALE meta-analysis, this study employed a machine learning algorithm. In particular, there are different algorithms in the machine learning field of study (Lantz, 2015). Using an appropriate algorithm based on correlation-based clustering in machine learning, this study developed a parsimonious model or brain map that explains consumers' decision-making process through analyzing the HCP datasets including behaviors (decision-making and emotions). Utilizing the meta-analysis and analyzing the fMRI image datasets, this study suggests a connectivity model, or an integrated brain map based on the neural interaction between brain regions for decision-making and emotions to support the argument that brain areas

for emotions are working with brain areas for cognitive behaviors when consumers make a decision including purchase or judgment for a decision.

This research consists of two main studies (Study 1 and Study 2) to develop a neural connectivity (map) for consumer decision-making process. Before conducting Study 1 and 2, two pilot studies will be undertaken to verify the goodness of fit of this entire research with another dataset of brain images of 900 subjects provided by HCP1. Pilot Study 1 verifies that there is a significant interaction between brain activities for a selected cognitive behavior (only language) and emotional behavior (only happiness) by conducting ALE meta-analysis that investigates commonly activated brain regions and underdeveloped brain regions for each of selected behaviors. Pilot Study 2 verifies a possible way of mapping the neural connectivity of brain regions activated for emotions with a smaller sample dataset of HCP1 including brain images from 900 healthy adults.

Main Study 1 looks for interactive neural areas activated for consumer decision-making and emotions based on the existing literature to answer for the first and second research questions by means of a meta-analysis of new and common findings from the existing literature related to emotions and consumer decision-making. Then, Main Study 2 uses the HCP1 dataset to verify the brain regions for activating specific cognitive (consumer decision-making) and emotional behaviors in comparison with the findings from Study 1. In Main Study 2, a brain map or functional connectivity for the consumer decision-making process was developed using machine learning algorithms based on the results of Main Study 1. Table 2 summarizes the structure of this research.

Table 2. Research Structure

Study	Purpose	Used method	Used dataset	Expected Outcome
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Pilot Study 1	Explore the relationship between cognitive and emotional behaviors	ALE-meta analysis (Caspers et al., 2010; Eickhoff et al., 2009)	10 existing studies for language and 10 existing studies for happiness	Most activated brain regions and new regions for each behavior
Pilot Study 2	Verify the interaction with empirical fMRI data	Graph theory Network theory	900 HCP1 fMRI dataset	Significant correlation coefficient (r) between two behaviors
Study 1	Find an interaction and new underdeveloped brain regions between consumer decision-making and emotions	ALE meta-analysis	Existing literature for each of emotions and decision-making	Most activated brain regions and new regions for each behavior
Study 2	Verify the interaction with empirical fMRI data Test the effect of individual personality on the decision-making process Develop a brain map that helps to explain and understand consumer decision-making process	Graph theory Network theory	1200 HCP1 fMRI dataset Findings of meta-analysis in Study 1	Significant correlation coefficient (r) between two behaviors Significant relationships and different patterns of brain activity among each behavior and personality Functional brain connectivity for emotional and cognitive behaviors

The findings of this research will theoretically and practically contribute to consumer research by finding patterns between consumer behavior and a specific brain area and verifying the pattern through archival data. This research will provide knowledge about the neurological and physiological aspects of consumer decision-making and the related cognitive and affective behaviors to the marketing discipline by empirically testing neuroimaging data. Most importantly, this research will provide a neural functional connectivity map of consumer

decision-making processes based on the comparison between brain activity for emotions and consumer decision-making.

The remainder of this study is structured as follows. Chapter II contains a literature review and a research framework for the study. The methods are described in Chapter III. Chapter IV presents the results, and a conclusion including a discussion of the theoretical and practical implications of the findings can be found in Chapter V.

CHAPTER II

LITERATURE REVIEW AND DEVELOPING RESEARCH FRAMEWORK

This research aims to find a parsimonious model that helps to understand how consumers make decisions and what physiological and neurological functions are included in the decision-making process through analyzing HCP1 datasets of fMRI brain images. This chapter takes a look at the existing literature to investigate important factors that affect the consumer decision-making process and to find theoretical relationships among each factor including memory, problem-solving, attention, pattern cognition, decision-making, and language as cognitive behaviors (Gasquoine, 2016; Reed, 2013) and feelings – fear, sadness, happiness, disgust, surprise, and anger – as emotional behaviors (Oatley, Keltner, & Jenkins, 2006; Gasquoine, 2016; Barrett, 2017).

A Short History of Consumer Neuroscience

Consumer neuroscience is defined as applying tools and theories from neuroscience to better understand decision-making and related processes. It is an interdisciplinary academic subfield of marketing and neuroeconomics (Plassmann et al., 2015; Shaw & Bagozzi, 2018). Consumer neuroscience is different from neuromarketing, which involves the practical implementation of neuroscientific knowledge for company marketing insights (Hubert & Kenning 2008; Ramsøy, 2014).

Research in consumer neuroscience has mostly focused on consumer decision-making based on analytics of functional activities in the brain using neuroscientific methods such as EEG

and fMRI (Kenning, Plassmann, & Ahlert, 2007; Yoon et al., 2012). These methods help the researcher in consumer neuroscience better understand consumer behaviors based on the physiological context that can provide explanations for observed phenomena or specific behaviors. For example, it is difficult to distinguish between and verify the role and effect of emotions in the process of decision-making by using traditional qualitative or quantitative measurements (Show & Bagozzi, 2018). Neuroscientific methods, however, have contributed to consumer research by providing significant results showing how the brain works physiologically and adding diversity and depth of knowledge of the neurological anatomy in terms of brain regions for emotional and cognitive activities.

Research on consumer decision-making using neuroscientific methods has expanded to understanding both inter- and intra-personal sources of heterogeneity, in terms of individual differences. This difference does not mean each consumer has the same process of decision-making, but each one has their own process by showing a pattern that interacts between genetic markers, hormone and neurotransmitter levels, and environmental variation (Sporns, 2011; Yoon et al., 2012). fMRI can identify brain regions that activate for the process based on the stimuli and support the assumption that every individual has his or her own process of decision-making based on his or her unique brain responses (Poldrack et al., 2009).

Insights and tools from neuroscience are of great value to consumer research, especially in understanding consumers' minds as the black-box (Shaw & Bagozzi, 2018). Plassmann et al. (2015) point out that neuroscientific methods are suitable to understand the processes and mechanism of consumer behaviors because neuroimaging tools can help validate, refine, or extend existing marketing theories. In other words, consumer research benefits by using tools that can demonstrate dissociations between psychological processes. In this vein, it is possible to

find scientific evidence supporting alternative consumer decision-making model that consumers are not only using cognitive abilities but also emotions when they attempt to make a decision.

With these advantages, consumer neuroscientific research has focused on consumer and decision neuroscience to elaborate cognitive behaviors (e.g., attention, memory, and reward processing) and emotional behaviors as shown in Table 3. As Table 3 shows, each study examines brain activity regarding specific behaviors. For instance, Noudoost, Chang, Steinmetz, and Moore (2010) found that the dorsolateral prefrontal cortex, inferior parietal sulcus, inferior frontal gyrus, middle temporal gyrus, posterior cingulate cortex, and precuneus activated for attention in a top-down way. Thus, this collaboration with neuroscientific research in consumer research has fruitfully contributed to increasing the breadth of knowledge of consumer behaviors by providing physiological evidence confirmed through neuroscientific research methods. In particular, consumer behaviors including emotions can be more deeply and sharply understood by the collaboration between consumer research and neuroscientific methods as a deconstructive way of extending a research scope of consumer behaviors.

Table 3. Literature on Consumer Neuroscience

Authors	Activity	Findings	Methods
Kastner & Ungerleider (2000)	Attention	Two primary modes of attention exist: bottom-up and top-down attention	fMRI
Duncan & Humphreys (1989)		The effect of environmental cues on the two primary modes	RT task
Connor et al. (2004)		The effect of environmental cues on top-down attention	Conceptual study
Huddleston et al. (2015)		The effect of eye movements on bottom-up attention	Eye tracker
Wolfe & Horowitz (2004)		The effect of expectation on top-down attention	RT task
Felleman & Van Essen (1991)		Key brain regions for bottom-up attention (insula, anterior cingulate cortex, and dorsolateral prefrontal cortex)	Conceptual paper

Noudoost et al. (2010)		Key brain regions for top-down attention (dorsolateral prefrontal cortex, inferior parietal sulcus, inferior gyrus, middle temporal gyrus, posterior cingulate cortex, and precuneus)	Conceptual study	
Kaas (2008)		Finding a main sensory (vision) process by comparisons among sensors	Conceptual study	
Armstrong et al. (2006)		Direct connection of prefrontal cortex to visual attention	Experiment/statistical simulation	
Milosavljevic et al. (2012)		Visual saliency influences food choice	Experiment/statistical simulation	
Eichenbaum (2004)	Memory	Multiple memory systems in the brain	Experiment	
Sperling (1963)		Sensory (visual) memory (visual information storage [VIS] and auditory information storage [AIS])	Experiment	
Baddeley (2017)		Short-term memory	Conceptual study	
McGaugh (2000)		Long-term memory	Conceptual study	
Doyon et al. (1998)		Striatum and cerebellum activation for long-term memory	Lesion study	
Murray (2007)		The function of the amygdala in the interaction between memory and negative events	Experiment	
Lynch (2004)		Patterned synapse activation in long-term memories	Conceptual study	
Smith & Vale (2006)		The hormone effect on memory	Conceptual study	
Ekman (1992, 2000)		Emotional Processing	The effects of subjective feelings in the decision-making process (1992) Facial expression (2000)	Conceptual study
Lindquist et al. (2012)			The functional areas for emotions in the brain	Functional clustering analysis (Kober et al., 2008)
LeDoux (2000, 2015)	The function of the amygdala in the negative emotions (fear)		Conceptual study	
Preuschoff et al. (2008)	Insular cortex activation for risk expectation		fMRI	
Sanfey et al. (2003)	Anterior insular cortex and dorsolateral prefrontal cortex activations for anger		fMRI	
Vytal & Hamann (2010)	Orbitofrontal cortex activation for anger		ALE meta-analysis	
Salamone & Correa (2012)	The function of nucleus accumbens in emotional processing		Conceptual study	
Murphy et al. (2003)	Anterior cingulate cortex activation for sadness		fMRI	

Kringelbach & Berridge (2012)	Reward Processing	The dopaminergic circuit associating with reward processing	Conceptual study
Fields et al. (2007)		The ventral tegmental area associating with reward processing	Conceptual study
Pool et al. (2016)		Systemic difference between wanting (incentive salience) and liking (hedonic) system	Meta-analysis
Berridge et al. (2009)		The neural wanting system (ventral tegmental area, nucleus accumbens, ventral pallidum, amygdala, anterior cingulate cortex, orbitofrontal cortex, and insular cortex)	Experiment with laboratory animals (rats)
Berridge & Kringelbach (2015)		Liking system (hedonic hot spot: nucleus accumbens and ventral pallidum)	Experiment with laboratory animals (rats)

Note: RT (reaction time)

Consumer Decision-Making

Decision-making is ubiquitous in daily life and is contingent on forming a preference, selecting and executing actions, and evaluating outcomes, which is a complex process involving all the stages from problem recognition to post-purchase activities (Donavan et al., 2016; Talukdar, Roman, Operskalski, Zwilling, & Barbey, 2018). Consumer research has focused on the process of decision-making because all individuals must choose among alternatives to fulfill their desires. Selecting one means losing another option that can be another way to fill out shortages or needs and wants. Thus, decision-making is important and continuous in consumer daily life. There have been three main arguments or perspectives in the consumer research related to understanding and describing the process of the choice: cognitive perspective, experiential perspective, and behavioral influence perspective.

The cognitive perspective assumes that all individuals are rational and practical thinkers who attempt to find an optimized option that satisfies their needs and wants (Bettman, 1979). Much of the research from this point of view has obtained similar findings or results that there

are crucial stages when people are looking to make a choice. The stages include recognizing a gap between what they have and what they want to have, researching alternatives, selecting one of the alternatives, evaluating the selection, and remembering the feedback. This process is called the information process (Bettman et al., 1998; Cacioppo et al., 1986; Reed, 2013). Thus, this perspective holds that decision-making is a process of searching, calculating, and manipulating the information of alternatives to find an optimized option that increases the level of consumers' expectation from the choice.

The experiential perspective is the antithetical point of view to the cognitive perspective and considers individuals as feelers rather than rational thinkers (Holbrook & Hirschman, 1982). In this perspective, consumers willingly behave and support the behavior based on their previous experience. In other words, through any experience in using products or services, consumers can accumulate abundant information that supports their behaviors including selecting a product or service or engaging in hedonic and impulsive purchasing behavior (Kozinets, 2001). Based on previous experiences, consumers justify and defend their behaviors including their choice of alternatives. Thus, in this point of view, emotions are important factors to understand and explain consumer decision-making because emotions are a core of evaluators in the process of decision-making (Dolan, 2002; Kramer, Mohammadi, Donamayor, Samii, & Munte, 2010; Pessoa, 2008).

The behavioral influence perspective focuses on behaviors of consumers and the contingencies of the environment that affect consumer behaviors in terms of consumer decision-making (Donavan et al., 2016; Mowen & Minor, 1998). For instance, the physical environment can be used to encourage certain behaviors. The use of textures, smells, lights, and store designs can have significant influences on behaviors when consumers are in a new place where they have never been before. Others' behaviors are also able to influence the consumer's behavior

including food choice or specific behavior in a new place. In a new traveling location, it may be difficult for consumers to make a good choice because of the lack of knowledge of the place. In this circumstance, there is a greater possibility that consumers will become a follower or imitator who is looking for appropriate ways or local behaviors that are commonly used and accepted in the place (Donavan et al., 2016). As these studies show, this point of view indicates that consumer decision-making can be affected by external factors as stimuli.

It is important for consumer research to verify the interaction between cognition and emotions as crucial factors that significantly affect consumers' decision-making process, no matter which perspective the researcher takes. However, it has been difficult to support the point of view that both emotions and cognition work coincidentally in decision-making because of decision-making environments and difficulty in empirically testing whether or not the factors are working together in the decision-making process (Plassmann et al., 2015; Show & Bagozzi, 2018; Yoon et al., 2006). The majority of consumer research on the decision-making process through neuroscientific methods has focused on judgment and brand choice (Plassmann et al., 2015; Smidts et al., 2014). The contribution of most of these studies is limited to accumulating knowledge about the brain areas and functions activated in the consumer decision-making process because there are limitations of looking at the neural regions activated for emotions even though emotions play an important role in the decision-making process. Table 4 provides the results of existing studies that have captured brain regions for specific behaviors.

Table 4. Consumer Research on Brain Regions Activated for Consumer Decision-making

Authors	Behaviors	Purpose	Method	Finding neural areas
Berns & Moore (2012)	Decision-making	Finding the neural signals of a small group of individuals when they decide to purchase	fMRI	Ventral striatum for purchasing behavior (decision)
Plassmann et al. (2012)	Brand choice	Overview of the current and previous research in neuromarketing area	Review	Striatum, ventral medial prefrontal cortex (vmPFC), and dorsolateral prefrontal

				cortex (dlPFC) for evaluation
Shaefer et al. (2006)	Brand choice	Finding the neural correlation of brand familiarity	fMRI	Medial frontal gyrus (MFG)
Esch et al. (2012)	Brand choice	Finding the neural areas activating for declarative and experiential information processes	fMRI	Pallidum for positive emotions and the insula for negative emotions
Huijismans et al. (2019)	Decision-making	Finding the effect of scarcity mindset effect on decision-making	fMRI	dlPFC and Orbitofrontal Cortex (OFC)
Jung et al. (2018)	Decision-making	Finding brain areas for prosocial behavior (social product purchase)	fMRI	ACC, dlPFC, vmPFC
Owens et al. (2017)	Decision-making	Rewarding effect on decision-making	fMRI	Middle Temporal gyrus (MTG)
De Martino et al. (2017)	Decision-making	Social information effect on judgement (decision-making)	fMRI	mPFC, vmPFC, dorsomedial (dm) PFC, ACC
Tong et al. (2015)	Decision-making	Trading experience effect on decision-making	fMRI	Anterior insula
Waskow et al. (2016)	Decision-making	Music effect on decision-making	fMRI	Lingual gyrus
Kühn et al. (2016)	Decision-making (judgement)	Sales promotion impact at point-of-sale on decision-making	fMRI	Nucleus accumbens, Medial Orbitofrontal Cortex, Amygdala, Hippocampus, Inferior Frontal Cortex
Cherry et al. (2015)	Decision-making	Healthy food choice and brain areas	fMRI	dlPFC
Lighthal et al. (2014)	Decision-making	Memory-dependent choice	fMRI	vmPFC
Yokoyama et al. (2014)	Decision-making	Finding brain areas for financial extravagance	fMRI	Caudate and Nucleus
Cartmell et al. (2014)	Decision-making	Finding brain areas for purchasing consumer goods	fMRI	Nucleus Accumbens (NAcc) and Anterior insula
Kang & Camerocer (2013)	Decision-making	Aversive decision-making brain areas (insurance purchase)	fMRI	Striatum, mPFC, Amygdala
Carsarotto et al. (2012)	Decision-making	Brand recognition and choice	fMRI	Amygdala and dlPFC
Creswell et al. (2013)	Decision-making	Product choice under budget pressure	fMRI	dlPFC, Intermediate Visual Cortex
Van den Laan et al. (2012)	Decision-making	Packaging effect on product choice	fMRI	Bilateral Striatum, Superior Frontal Gyrus, Middle Occipital Gyrus
Kang et al. (2011)	Decision-making	Purchasing products in different situations	fMRI	OFC and Ventral Striatum
Levy et al. (2011)	Decision-making	Value reward effect on decision-making	fMRI	Striatum and mPFC

Tusche et al. (2010)	Decision-making	Attention on choice (purchase a car)	fMRI	Insula and mPFC
Grosenick et al. (2008)	Decision-making	Predictors of purchase	fMRI	NAcc and mPFC
Bray et al. (2008)	Decision-making	Influence of Pavlovian cues on decision-making	fMRI	Ventrolateral Putamen
Knutson et al. (2007)	Decision-making	Predictors of purchase	fMRI	NAcc and mPFC
McClure et al. (2005)	Decision-making	Cultural preference on decision-making	fMRI	vmPFC
Al-Kwafi (2016)	Brand attitude and decision-making	Finding the neural areas activated for brand attitude toward switching a product brand	fMRI	vmPFC

Note: This table does not include studies looking for neural signals for consumer behaviors by other neuroscientific methods, such as EEG/MEG. ventral medial prefrontal cortex (vmPFC), dorsolateral prefrontal cortex (dlPFC), medial prefrontal cortex (mPFC), inferior prefrontal cortex (IFC), middle temporal gyrus (MTG), anterior cingulate cortex (ACC), Orbitofrontal Cortex (OFC), Nucleus Accumbens (NAcc)

To summarize previous studies on the consumer decision-making process, there has been a pattern of activated brain regions for decision-making in terms of different areas in the prefrontal cortex (PFC), such as ventromedial prefrontal cortex (vmPFC), medial prefrontal cortex (mPFC), dorsomedial prefrontal cortex (dmPFC), and dorsolateral prefrontal cortex (dlPFC). Other brain regions for the behavior (decision-making) frequently included nucleus accumbens (NAcc) and striatum. Some brain regions, such as the insula and amygdala, are mainly activated for emotions (Barrett, 2017; Singer, Critchley, & Preuschoff, 2009). The following section reviews previous research related to consumer decision-making focusing on emotions categorized by six different types of feelings.

Emotions

Emotions are subjective feelings, such as happiness, fear, or anger. Emotion has been a topic of discussion in many different disciplines for over 2000 years. Thus, it has been through a tough time that scholars who are conducting research on emotions disagree in their definitions of emotion (Oatley et al., 2006) because definitions are too heterogeneous. However, in a debate of

defining the concept of emotion there is a common argument that emotions serve important functions in mechanisms that regulate controllable biological processes and psychophysiological reactions to help individuals achieve their goals through establishing, maintaining, and/or disrupting significant relationships between an organism and the external and internal environment (Barrett, 2017; Keltner & Gross, 1999).

According to Shaw and Bagozzi (2018), there are two different points of view about emotions: the locationist approach and psychological constructionist approach. The locationist approach holds that discrete emotional categories are associated with specific brain areas, while the constructionist view hypothesizes that emotional processes are created from interactions between general neural networks that are not associated with emotional categories. Barrett (2017) and Ekman (1992) noted that these feelings can be a way of expressing how we sense and understand in a specific circumstance or moment in a time. However, the vast majority of past research on emotional processing within the brain relies on the locationist approach.

Using neuroimaging methods including fMRI and positron emission tomography (PET), researchers have found brain regions activated and regulated for specific behaviors. For instance, the medulla controls cardiovascular activity, the pons regulates human sleep, the cerebellum is involved in controlling motor movement, the thalamus is involved in integrating sensory information, the hippocampus is critical for memory processes, and the hypothalamus regulates important biological functions such as eating, sexual behavior, aggression, and bodily temperature (Oatley et al., 2006). A vast number of studies on emotions in neuroscience including neuropsychology and neurology agree that emotions are mediated by specific brain regions such as the amygdala (Chanes & Barrett, 2016; Costafreda, David, & Brammer, 2008; Kragel & LaBar, 2016; Loewenstein & Lerner, 2003, Oatley et al., 2006).

In consumer research specializing in consumer neuroscience, Loewenstein and Lerner (2003) theoretically argued that emotions play an important role in decision-making. Since the 1960s, decision-making has largely adhered to the cognitive perspective that considers individuals as rational thinkers who attempt to make a decision by a cognitive process or by information process. Loewenstein and Lerner hypothetically developed and suggested a decision-making process in which emotions are important factors significantly influencing individuals' decisions.

With the exception of Ariely and Burns (2010) and Harris, Ciorciraci, and Gountas (2018), there is not much research in the field of business disciplines on the role of emotions in consumer or organizational behaviors using neuroscientific methods including fMRI, PET, MEG, and EEG because of diverse circumstances and purposes of studies in the discipline. Despite the limited use of neuroscientific methods in the business disciplines and the lack of understanding of the importance of emotions in the decision-making process in consumer research, studies in the marketing discipline have been heavily skewed in the direction of finding brain regions associated with specific behaviors such as decision-making and brand/product choice (Plassmann et al., 2015; Shaw & Bagozzi, 2018).

Shaw and Bagozzi (2018) describe that each brain region has activated for or controlled each emotion: the amygdala for negative emotions, insular cortex for anger and disgust, and orbitofrontal cortex (OFC) for anger and regret feelings. Spunt and Adolphs (2019) found different neuro functional components of how people understand others' emotions. Using neuroimaging analysis, they found brain regions activated for understanding others' emotions including the anterior temporal cortex (aTC), posterior superior temporal sulcus (pSTS), dorsomedial prefrontal cortex (dmPFC), and ventrolateral prefrontal cortex (vlPFC). The

amygdala plays an important role in regulating emotions (LeDoux, 2000; Rilling & Sanfey, 2011). Therefore, the research looks at the previous literature for emotions, its role, and brain regions.

Categories of emotional behaviors (focused on brain regions for feelings)

There are subjective feelings in emotions according to the locationist point of view as the majority group in neuroscience (Shaw & Bagozzi, 2018). This section offers descriptions of each aspect of emotions and the associated brain region based on the review of existing literature in the marketing discipline as well as other fields. Although there are still many discussions about the diversity of affects (Damasio, 1994; 2003), this study mainly follows the category of affects in emotions discussed by Barrett (2017), Ekman (1972), and Gasquoine (2016).

Fear. Fear is a vital response to physical and emotional danger (Strange & Dolan, 2006). People store information about unpleasant events or experiences in their memory (Brugger et al. 2011). This information is a source that stimulates them to remember the event or experience, and feelings are the expression of the memory. Thus, feelings are highly associated with cognitive behaviors such as memory and its process. To detect brain regions for fear, Brugger et al. (2011) used dental service or treatment as a stimulus because patients have strong memories of dental treatment, especially taking out teeth in a dental office. In their experiment, Brugger et al. showed the process of how people feel fear when they are exposed to a painful event or environment and which brain regions activated for the fear. They found the brain areas for fear: amygdala in left hemisphere (LH), cerebellum anterior lobe in both right and left hemispheres (RH and LH), caudate in LH, hippocampus in both LH and RH, thalamus, postcentral gyrus, posterior insula, putamen, and supplementary motor area. Brugger et al. had a limitation that

each tooth is related to a different brain area reacting to the pain, thus it was hard to see the primary brain region activated for the fear from painful stimulus. However, they showed that the cingulate cortex subdivisions (Posterior cingulate cortex: PCC, Posterior middle cingulate cortex: pMCC, Anterior middle cingulate cortex: aMCC, Pregenuar anterior cingulate cortex: pACC, and Subgenual anterior cingulate cortex: sACC) significantly activated for fear.

Happiness. According to Argyle (2002), happiness can be measured by the difference between subjective well-being and objective well-being. This is similar to Oliver's (1980) attempt to measure customer satisfaction through calculating the gap between expectancy and disconfirmation. However, Argyle's point of view on happiness is not only about individual feeling as an aspect of emotions but also about socioeconomic evaluation as objective well-being. He looked at happiness as a construct containing various factors that explain happiness. This point of view is helpful to understand how the affect is made through the theoretical process.

Neuroscientific studies on positive affect or happiness show the brain areas that activate for the affect. Burgdorf and Panksepp (2006) found that the ventral striatum is recruited in multiple forms of positive affective states. Knutson, Fong, Adams, Varner, and Hommer (2001) discovered that increasing metabolic activity is positively associated with the ventral striatum while the actual receipt of a monetary reward is related to a decrease in ventral striatal activity. Kringelbach et al. (2003) found that the orbital frontal cortex activated for positive emotional states related to taste- and olfactory-induced positive affect (PA). In particular, the frontal cortex in the right hemisphere is positively associated with PA in humans (Burgdorf & Panksepp, 2006).

Another brain region related to PA is the amygdala. Adolphs, Tranel, and Damasio (2003) found the area activated for a negative affect (NA) rather than PA. This finding is supported by Holstege et al. (2003), who showed that amygdala activation decreases when humans' PA induced stimuli such as music, odor, self-generated PA, and male orgasm. However, Murray (2007) argued that the amygdala activated when people recognized that they are rewarded. Diano et al. (2017) also contradicted the previous point of view that amygdala activation related to NA by showing the area is also positively associated with PA.

Sadness. Sadness is an emotional reaction to a perceived hurt from physical loss to mental loss (Reevy, 2010). It lasts anywhere from a few seconds to several hours or days. In a multicultural study of emotions, Scherer (1997) argued that sadness is associated with some level of hopelessness that results from events including the death of a loved one, loss of a relationship, job, or home, or receiving a low score on an exam. Like other emotions such as fear, sadness is clearly functional, leading to self-protective or self-promoting behaviors such as escaping from danger or mating (Thompson & Boden, 2019). Consumer research has also supported the role of sadness and its effect on consumer behaviors such as judgment and preference. Motoki and Sugiura (2018) found different effects of negative emotions including sadness on food choices, while Lerner et al. (2015) pointed out that emotions, especially positive appraisal mood, enhance consumers to shape a choice by impacting the judgment process of understanding and interpreting others' opinions or reviews.

Neuropsychology studies show the brain regions activated for sadness. Brattico et al. (2011) investigated brain region activated for both positive and negative emotions when people are exposed to music without lyrics such as background music in stores. They found that the insula, inferior and superior temporal gyri, anterior cingulate, middle frontal gyrus, cingulate

gyrus, inferior frontal gyrus, and amygdala are linked to emotional reactions toward both sad and happy music. Barrett, Pike, and Paus (2004) tested the role of the anterior cingulate cortex (ACC) when people equated upset with sad and discovered that sad affect is positively associated with the brain region (ACC). Habel, Klein, Kellermann, Shah, and Schneider (2005) examined the correlations of brain activity or reactions for sad and happy mood; for sad mood, ventrolateral prefrontal cortex (vlPFC), the anterior cingulate cortex, the transverse gyrus, and the superior temporal gyrus are more activated than other areas in the brain.

Disgust. According to the *Merriam-Webster Dictionary* (2019), disgust as a feeling or emotional reaction is defined as a marked aversion aroused by something highly distasteful. Baduor and Feldner (2018) defined disgust as an emotional response of rejection or revulsion to something potentially contagious or something considered offensive, distasteful, or unpleasant. In their point of view of disgust, the affect is linked to internal and/or external factors such as posttraumatic stress and trauma.

In marketing research, disgust has been considered a critical factor that changes consumer behaviors, especially consumer attitudes. Morales and Fitzsimons (2007) tested the effect of physical contact of product contagion on changing consumer evaluations about the product and found that physical contact was a moderator or external stimulus to change the level of disgust. Shimp and Stuart (2004) viewed the emotional response of disgust as a mediator in the relationship between advertising as a marketing communication and fast-food consumption. Hamerman and Schneider (2018) supported the view of disgust as a factor that affects consumer decision-making, especially in the process of deciding to participate in volunteer work. Palomo-Velez, Tybur, and Van vugt (2018) also supported this role of disgust in a study of persuasive advertising messages against meat consumption.

Corradi-Dell'Acqua, Tusche, Vuilleumier, and Singer (2016) found the anterior insula (AI) and mid-anterior cingulate cortex (mACC) were repeatedly implicated in experiences of pain, disgust, and unfairness. Another study on the brain activation for disgust shows there are several regions activated for the emotional response: fusiform gyrus, medial frontal gyrus, inferior frontal gyrus, superior frontal gyrus, and middle temporal gyrus (Oaten et al., 2018). Schienle, Hofler, Ubel, and Wabnegger (2018) found the effect of disgust in the process of determination and showed that the left orbitofrontal cortex (OFC) is actively linked to disgust. Especially, they found amygdala and insula are also activated for the emotional response.

Anger. Anger is considered one of the basic emotions and has been an important subject in behavioral studies. It is antagonism toward someone or something one feels has deliberately done wrong (Kazdin, 2000). It is argued that anger can be a good thing because it can give a way to express negative feelings and motivate to find solutions to problems. On the other hand, excessive anger causes problems because increased blood pressure and other physiological changes associated with the emotional response (Kazdin, 2000) as well as making it difficult to think straight and harming physical and mental health.

In consumer research, anger has been a relevant topic and played an important role in consumer behaviors, especially in the process of decision-making. Walter, Tuakchinsky, Pelled, and Nabi (2019) conducted a meta-analysis study on anger and its effect on persuasion to show that anger appeal messages increase the power of persuasion, result in a strong argument, and lead to the presence of strong argument. Su, Wan, and Wyer (2018) empirically examined fear and anger as emotions that come after experiences of service failure and found that these negative emotions can lead to service change or switching behaviors and negative word-of-mouth as negative customer engagement. With this point of view, Khan, DePaoli, and Maimaran

(2019) argued that dealing with customer's negative emotions helps customers choose a product or service because customers attempt to avoid an uncomfortable condition or environment. Thus, anger may influence goal-directed decision-making.

Anger as part of the consumer decision-making process presents in diverse brain regions (Buades-Rotger, Beyer, & Krämer, 2017). Buades-Rotger et al. found that the orbitofrontal cortex (OFC), amygdala, and sensorimotor cortex were more active when participants decided to fight with others, while other brain locations such as medial and inferior frontal gyrus (IFG) and temporal parietal junction (TPJ) were relatively less active. Alia-Klein et al. (2018) found that the emotional response of anger modulates neural activity in the middle occipital gyrus (MGO), inferior frontal gyrus (IFG), middle-frontal gyrus (MFG), mid-insula, and inferior parietal lobule (IPL) in the left hemisphere of the brain. Kim et al. (2018) showed that young adults (aged 18 to 22) have increased brain activity in the amygdala and dorsolateral prefrontal cortex (dlPFC) when they are exposed to a traumatic situation. Heesink et al. (2018) found heightened activity in the supplementary motor area and the cingulum and parietal cortex, with stronger connectivity between the dorsal anterior cingulate cortex (dACC) and amygdala activated for aggression as a behavioral expression of anger.

Surprise. Surprise is usually induced by sudden or unexpected events (Nguyen, 2013). Typically, it is very visible on an individual's face, including widening of eyes, opening of the mouth, and gasping (Oatley et al., 2006). Surprise may be generated by positive or negative factors (Havlena & Holbrook, 1986; Laros & Steenkamp, 2005). A majority of researchers in consumer research posit that surprise is a positive or pleasant reaction to sudden and unexpected events (Havlena & Holbrook, 1986; Hsu et al., 2016; Westbrook & Oliver, 1991). Thus, they consistently pointed out that surprise can lead to customer satisfaction and show that marketing

actions can be a positive influencer that helps customers who have low expectations of a product or service change the level of satisfaction or overall evaluation including judgments when they are exposed to marketing actions that cause surprise as a positive emotional response (Crotts & Magnini, 2011).

Regarding surprise as an emotional response, Vrticka et al. (2014) showed brain imaging evidence that the amygdala plays a key role in understanding surprise as an emotional response to novel stimuli. They also probed the brain region involved in the processing of information about either negatively and positively surprised facial expressions. Bartolo, Benuzzi, Nocetti, Varaldi, and Nichello (2006) found the right inferior frontal gyrus (IFG), the left superior temporal gyrus (STG), the left middle temporal gyrus, and the left cerebellum were actively linked to the emotional response and the information process in both right and left hemispheres. Egner, Monti, and Summerfield (2010) found the neural activity for surprise in the fusiform face area (FFA) located in the inferior temporal cortex (IT) as Kanwisher, McDermott, and Chun (1997) logically argued.

Functional Connectivity

Understanding the brain's activity and functions has been a prominent and ongoing research agenda for over a century (Sporns, 2011; Shaw & Bagozzi, 2018). One of the oldest debates in neuroscience centers on whether specific mental functions are localized to specific brain regions or instead rely more diffusely upon the entire brain (Poldrack, Mumford, & Nichols, 2011). Today, nearly all neuroimaging research is centered on functional localization (Glasser et al., 2016; Poldrack et al., 2011). Thus, it has been important to analyze brain

connectivity with fMRI data that provide a means to understand how spatially distant brain regions interact and work together to create mental function (Friston, 2005).

Functional connectivity is defined as correlations in activity between spatially isolated brain areas. The connectivity arises for a number of reasons (Sporns, 2011). There are three different types of connectivity: effective connectivity, meaning the direct influence of one region on another; indirect connectivity, indicating the influence of another region that is mediated by a third region; and shared influence that reflects a common input to both regions. Neural interconnections transfer information within the brain, so there is a strong relationship in the brain functions (Smith et al., 2013; Arslan et al., 2018). Thus, human connectomics studying brain connectivity in functional and structural relationships among brain regions is an emerging scientific concept to describe the structural and functional connectivity patterns of the human brain (Cao et al., 2014).

According to Poldrack and his colleagues (2011), there are three different types of approaches in connectivity studies: functional connectivity, which seeks the correlations in brain activity between spatially remote brain regions; effective connectivity that attempts to bridge the explanatory gap from understanding functional connectivity by testing causal models of the interactions between regions; and network analysis, which examines the complex networks of the brain's functions based on social network theory. This study takes the approach of functional connectivity based on network analysis to see the complex relationships among different neural behaviors including various types of emotions and cognitive neural activity and to find a pattern of neural activity for both emotions and cognition.

Network theory

Networks are all around us. Individuals naturally organize themselves into networked systems. Families, neighborhoods, communities, and society surround each individual. A market consists of the combination of each consumer's networks. To look for connection patterns among people or geographical places, Social Network Theory (SNT) has been developed with graph theory in Mathematics. SNT started with the discussion of solving the problem in going through all other points to a destination on a bridge, known as bridge of Koenigsberg (Euler, 1953). Since then, the theory has been applied in different fields of social study, such as psychology, business, and education (Luke, 2015). For instance, it helps us to better understand the theory of diffusion of innovation (Rogers, 2010), Google search, and social network services (SNS, such as Facebook and Twitter).

SNT is especially beneficial to clearly understand and develop the connectome among brain regions activated for all cognitive and emotional behaviors including decision-making, language, memory, and all types of feelings. Watts and Strogatz (1998) used the theory to explain brain connectivity or neural networks as Small World initiated by Milgram (1967). Poldrack et al. (2011) and Sporns (2011) also introduced the theory as a way of mapping structural neural connectivity and functional neural connectivity based on brain activity and regions. SNT employs graphs showing a pattern of networks or a network itself. A graph consists of nodes as core components of the network (known as regions of interest, ROI) and edges as links between nodes and shows the connection between nodes and edges. The degree of nodes is the number of edges (Poldrack et al., 2011, p. 155).

It is important to understand and utilize the theory with understanding the concept of centrality as the robustness of network. Centrality refers to how closely components of a network are connected. Network robustness indicates the degree of resistance against the lack of

connection in the network, in terms of the degree of a strong connection among components. Thus, if a network has strong robustness, it is unlikely to lose the power of connecting each component in the network (Scott, 2000). This indicator of network strength is helpful to show different patterns of connecting each component as topological structures including ring, mesh, star, fully connected, line, tree, and bus type connection (Luke, 2015). Therefore, SNT is important for this study whose purpose is to develop and support a model of the consumer decision-making process by identifying functional neural connectivity based on the brain activity related to cognitive and emotional behaviors.

The Association between Decision-Making and Emotions and Its Connectivity

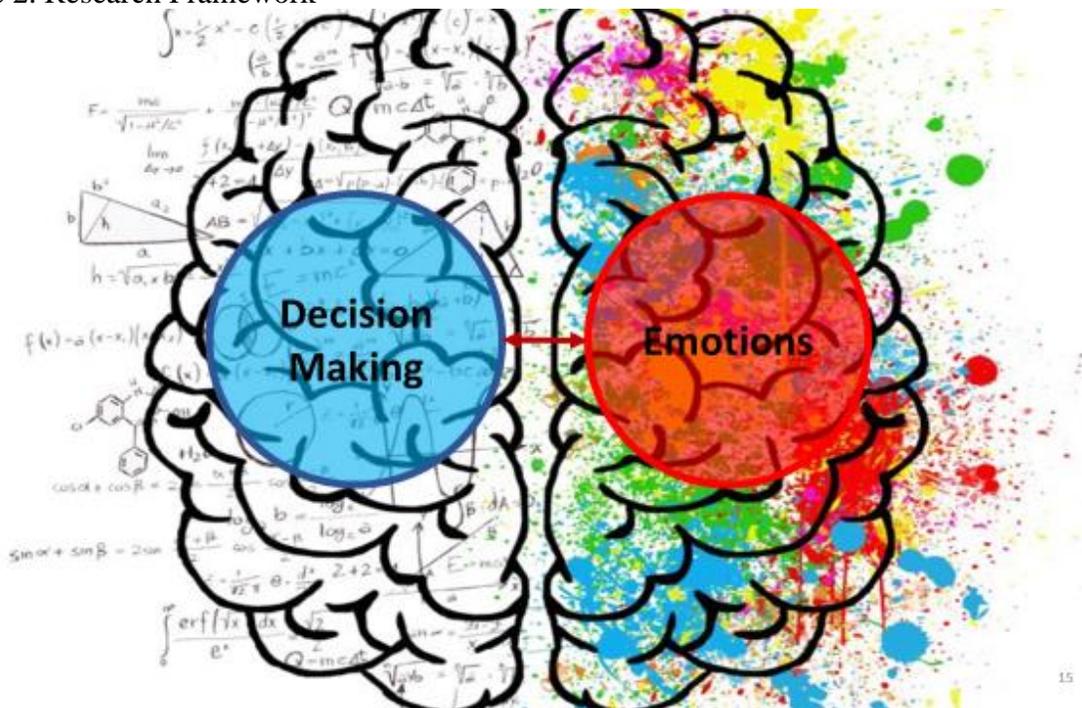
It is relatively difficult to verify the relationship between cognition and emotions because each construct is broad and has different characteristics and because it is hard to directly measure both cognition and emotions. From the neuropsychological point of view, cognition and emotions are behaviors which are considered as a result or a dependent variable (Gasquoine, 2016; Reed, 2013). Thus, this study focuses on a type of relationship between cognitions and emotions. As noted by Hirschman and Holbrook (1982) and Loewenstein and Lerner (2003), emotions play a significant role in consumers' decision-making process. Hirschman and Holbrook (1982) pointed that emotions play an important role in decision-making because experience of using products affects building consumer attitude toward the product. With this point of view, Loewenstein (2017) argued that surprising people have intended to share and provide their opinion based on their emotional experience to persuade others.

The debate about whether the decision-making process is cognitive or experiential has been going as long as the discussion on the relationship between cognition and emotions

(Loewenstein & Lerner, 2003). Traditional decision theory based on the argument that consumers or individuals make a decision by the information process (Bettman 1979; Bettman et al., 1998) has been dominant in many different fields (Loewenstein & Lerner 2003). However, Dolan (2004) and Pessoa (2008) argue that emotion influences individual behaviors including speaking and decision-making as aspects of cognition. Loewenstein and Lerner also propose a theoretical model that aims to explain how emotions influence and work in decision-making. They suggest that theoretically emotions can be considered as a factor that affects decision-making behavior. This theoretical relationship of emotions in the decision-making is presented in Figure 2. Therefore, based upon these arguments in the existing literature, this study theoretically proposes a research hypothesis (RH) as follows:

RH. When consumers decide on or purchase a preferred brand or a product by the information process (sales promotion-price discount and budget pressure), brain areas for decision-making including dlPFC, NAcc, dmPFC, and vmPFC are highly activated with the brain areas for emotions including amygdala, anterior cingulate cortex (ACC), orbitofrontal cortex (OFC), and insula.

Figure 2. Research Framework



Note: Blue circle indicates brain activity for decision-making, and red circle means brain activity for emotional behaviors such as sadness, happiness, disgust, anger, surprise, and fear.

CHAPTER III

METHODOLOGY

This chapter will present the methods for this research and introduce the datasets used for each study. The research consists of two different studies: Study 1 looks for an interaction among brain activity for both cognitive and emotional behaviors, and Study 2 investigates brain functional connectivity based on the findings of Study 1 and image analysis of archival HCP fMRI image data. In detail, Study 1 employs the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) statement, and Activation Likelihood Estimation (ALE) meta-analysis, which is a new and increasingly popular type of meta-analysis for neuroscience research. Study 2 employs various statistical software programs to develop and visualize a brain map based on brain functional connectivity, specifically MAPLE, MATLAB, NetMinor, and R based on Graph (network) theory.

Systematic Review (PRISMA, Study 1)

A systematic review attempts to collect all empirical evidence that fits pre-specified suitability criteria to answer specific research questions. It uses unambiguous and systematic methods that are selected with a view to minimizing errors, thus providing reliable findings from which conclusions can be drawn and decisions made (Oxman & Guyatt, 1993). The vital characteristics of a systematic review are (a) a clearly stated set of objectives with a clear and

reproducible methodology, (b) a systematic search that attempts to identify all studies that would meet the eligibility criteria, (c) an investigation of the validity of the findings of the included studies, and (d) systematic presentation and synthesis of the characteristics and findings of the included studies (Liberati et al., 2009).

Systematic reviews and meta-analyses are indispensable tools for summarizing evidence accurately and reliably. They help researchers keep up-to-date, provide evidence, and find new insights. The clarity and transparency of literature reviews, however, are not always optimal (Liberati et al., 2009). Low quality of reports from systematic reviews diminishes the values that they found. The first development which generated high quality of systematic reviews was the Quality of Reporting of Meta-analysis (QUOROM) (Moher et al., 2000). An international group of scholars including authors and methodologists built on QUOROM to develop the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) Statement (Liberati et al., 2009), a 27-item checklist with a four-phase flow diagram. The study employed PRISMA to minimize a researcher bias that may have a negative impact on the results and findings from a systematic review.

The QUOROM Statement was developed in 1996 and published in 1999, targeted to researchers who wanted to study and report a meta-analysis of randomized trials (Liberati et al., 2009). In fact, the statement or the systemic review contributed to piling up knowledge about conducting literature review, noticeably. By updating the QUOROM Statement, Liberati et al. (2009) developed and changed the name of the reporting guidance to Preferred Reporting Items for Systematic reviews and Meta-Analysis (PRISMA). The PRISMA statement was developed by a group of 29 experts including review authors, methodologists, clinicians, medical editors, and consumers (Moher et al., 2008). Through a three-day meeting, the group of experts

developed and guided a 27-item checklist and a four-phase flow diagram. This itemized checklist helps research explicitly explain the meaning and rationale for selected studies (Moher et al., 2008 & 2015).

Literature search (inclusion criteria)

Based on the criteria and the procedure of conducting PRISMA suggested by Liberati et al. (2009), this study searched and selected studies from PubMed and Google Scholar based on several important key words (fMRI, consumer decision-making, and different types of emotional expressions such as happiness, sadness, anger, disgust, fear, and surprise). In order to select the most relevant studies on brain regions activated for consumer decision-making and emotions, this study used specific search terms only including fMRI experiments, the target behaviors (consumer decision-making, fear, happiness, anger, disgust, surprise, and sadness), healthy people as participants of each fMRI experiment, and Montreal Neuroscience Institute (MNI) coordinates. The search was conducted in March 2019.

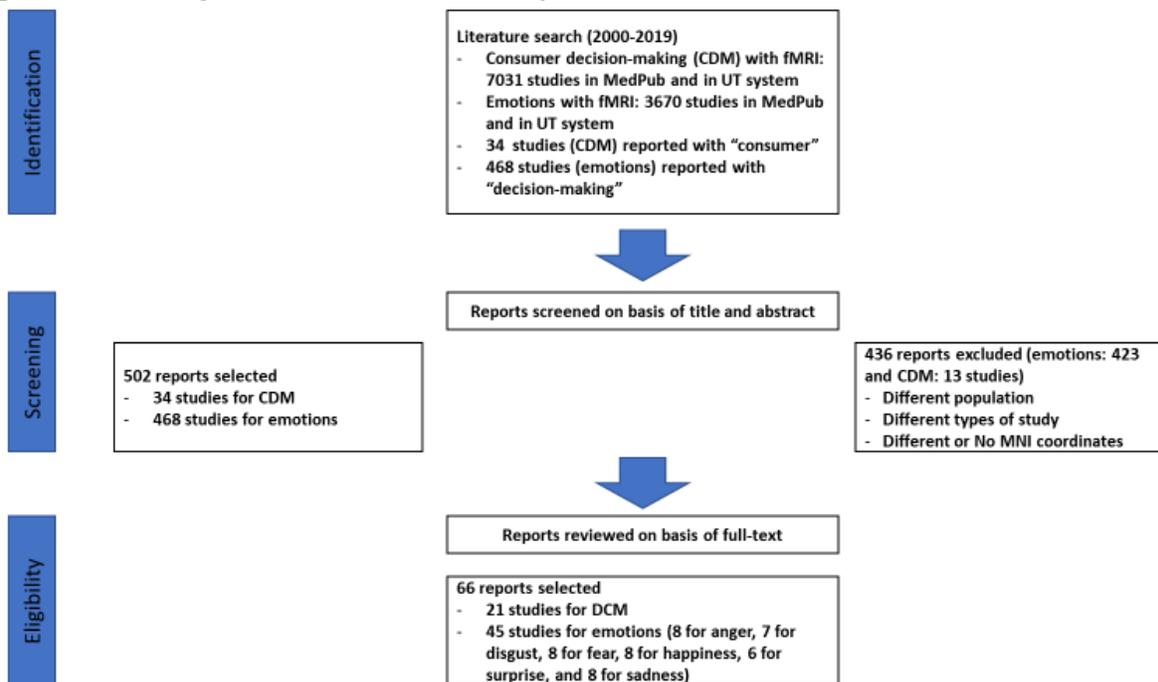
Study selection

Initially, this study used US National Library of Medicine, PubMed, to more precisely select studies for the meta-analysis of studies of brain regions activated for consumer decision-making. As the first step of PRISMA, fMRI and consumer decision-making were determined as the key terms for a search. This step identified 34 studies using the key terms. Then, using the key term, which is MNI, 21 studies were finally selected for meta-analysis for consumer decision-making as shown in Table 10. A total of 13 studies were removed because they used a

different population group (patients), different coordinates (or no coordinate information), or were an irrelevant type of study (review).

The same method was used to collect studies on the brain regions activated for each emotion, resulting in 228 studies using the search terms fMRI and sadness, 350 studies using fMRI and happiness, 2117 studies using fMRI and fear, 231 studies using fMRI and surprise, 464 studies using fMRI and anger, and 280 studies using fMRI and disgust. Especially, to have more accurate selection of studies for emotions, this study conducted another search using the terms, MNI and (consumer) decision-making. This step provided 8 studies for anger, 7 for disgust, 8 for fear, 8 for happiness, 6 for surprise, and 8 for sadness. The purpose of this study is to look for the physiological interaction between brain regions activated for each of consumer decision-making and emotions in the brain. Thus, through this selection procedure of PRISMA, total 46 studies were selected for emotions. The list of selected studies is presented in Table 12. The entire process of PRISMA is described in Figure 3 as follows.

Figure 3. Summary of Literature Search Adapted from PRISMA



This study had two reviewers assess and identify the criteria and one to settle disputes. To verify the selection of studies, three volunteers reviewed the process of selecting studies and determined any errors in the process. Each of them proceeded with same search terms. Study eligibility based on an initial title and abstract screen was determined independently by two reviewers (HWK and YSC from Math Department and Engineering Department at UTRGV, respectively) to assess and identify relevant inclusion criteria such as fMRI experiments, consumer decision-making, each emotion (fear, disgust, sadness, surprise, happiness, and anger), MNI coordinates, and healthy participants. Studies that potentially met the inclusion criteria were further evaluated by reviewing their full texts. Articles were excluded if both reviewers decided that the articles clearly did not meet the criteria. A third reviewer (JWK from Management Department at Georgia Southern University) resolved disagreement by independently assessing the remaining articles based on the criteria.

Data Collection Process

Information was extracted and selected using a spreadsheet with the following headlines: first author, title, year of publication, number of participants, age, gender, study design, assessments, results, and risk of bias by following a previous study conducted PRISMA (Durand et al., 2019). Only 66 studies were selected through PRISMA process. All studies and reports included all criteria. At least 7 experiments, which is the recommended number of studies, for each of decision-making, sadness, happiness, anger, surprise, fear, and disgust are required to conduct activation likelihood estimate (ALE) meta-analysis (Acikalin, Gorgolewski, & Poldrack, 2017; Eickhoff, Bzdok, Laird, Kruth, & Fox, 2012; Eickhoff et al., 2009), providing region of interest (ROI) and MNI coordinates of activated brain regions.

Activation Likelihood Estimation (ALE) Meta-analysis (Study 1)

A variety of meta-analytical methods (coordinate-based and image-based) have been developed to help summarize and integrate the vast amount of data from neuroimaging studies (Muller et al., 2018). Image-based meta-analysis (IBMA) makes use of all the information from the images. IBMA allows for the use of hierarchical mixed effects models that account for intra-study variance and random inter-study variation (Salimi-Khorshidi, Nichols, Smith, & Woolrich, 2009). However, because whole-brain statistical images are rarely shared, most meta-analytic research cannot answer a specific research question with IBMA.

In contrast, coordinate-based meta-analysis (CBMA) only uses the [x, y, z] coordinates of each peak location reported. Most individual neuroimaging studies provide their results as coordinates in a standardized anatomical space named either MNI or Talairach, but CBMA uses a sparser representation of findings. CBMA thus allows neuroimaging researchers to capitalize on the published neuroimaging literature and provide a quantitative summary of the results to answer a specific research question that cannot be answered by IBMA (Muller et al., 2018). There are several different approaches in CBMA: kernel density analysis (KDA; Wager, Jonides, & Reading, 2004), Gaussian process regression (GPR; Salimi-Khorshidi et al., 2011), activation likelihood estimation (ALE; Eickhoff et al., 2009; Eickhoff et al., 2012, Turkeltaub et al., 2002), parametric voxel-based meta-analysis (PVM; Costafreda et al., 2009), and signed differential mapping (SDM; Radua & Mataix-Cols, 2009).

To verify the interaction between cognition and emotions, this study employed activation likelihood estimation (ALE) meta-analysis (Eickhoff et al., 2009; Eickhoff et al., 2012), a widely used technique for coordinate-based meta-analyses of neuroimaging data. ALE assesses the

overlap between foci based on modeling them as probability distributions centered at the respective coordinates (Eickhoff et al., 2009). ALE maps are then obtained by computing the union of activation probabilities for each voxel. To differentiate true convergence of foci from random clustering, a permutation test is employed, and coordinates are then demonstrated with a Gaussian function to accommodate the spatial uncertainty associated with a reported coordinate and analyzed to see where they congregate (Laird et al., 2009).

This method is based on the clustering analysis that looks for adjacent and significant spots close to a target point. The Euclidean method is used to calculate the distance between

$$\text{points of each activated brain region at } \sigma_{sub} = \alpha_{sub} = \frac{ED_{sub}}{2 * \sqrt{\frac{2}{\pi}}} \text{ and } \sigma_{temp} = \alpha_{temp} = \frac{ED_{temp}}{2 * \sqrt{\frac{2}{\pi}}}$$

where ED_{sub} is the Euclidean distance between corresponding foci of different subjects and ED_{temp} is the mean Euclidean distance between corresponding maxima as observed in the different group-analyses. In order to model the spatial uncertainty linked with a presented focus, these EDs are transformed into the equivalent kernel sizes of Gaussian distributions used in ALE analysis. For this procedure, an isotropic normal distribution of all displacements relative to the true locations must be assumed, meaning that ED_{sub} and ED_{temp} reflect the average distance between locations where there are independent realizations of an isotropic and stationary Gaussian displacement across voxels (Eickhoff et al., 2009). In the basic form of Maxwell-

Boltzmann distribution, known as $[\mu = 2\alpha\sqrt{2/\pi}]$, each of the three underlying normal distributions (x, y, z displacement) has a mean of 0 and a standard deviation of α .

Given the σ of a Gaussian distribution, the full width at half maximum (FWHM) can be calculated to blur the foci as follows:

$$FWHM_{sub} = \sigma_{sub} * \sqrt{8 * \log(2)} \text{ and } FWHM_{temp} = \sigma_{temp} * \sqrt{8 * \log(2)}$$

Since measuring error in Gaussian distributions rulers inversely to the square root of the number of observations, an approximation of the spatial uncertainty can be estimated as

$$FWHM_{sub(effective)} = \frac{FWHM_{sub}}{\sqrt{N_{subjects}}}$$

To obtain the spatial uncertainty of a given coordinate, the two components shown above must be combined into one Gaussian distribution. The final FWHM used to derive the uncertainty in spatial location of the activations reported in a study is given by

$$FWHM_{effective} = \sqrt{(FWHM_{temp})^2 + \left(\frac{FWHM_{sub}}{\sqrt{N_{subjects}}}\right)^2}$$

Thus, larger subject sizes get a tighter and taller Gaussian distribution meaning that errors are minimized.

Following the suggestion of Muller et al. (2018) about how to effectively and efficiently use meta-analyses of neuroimaging data, this study focused on using ALE meta-analysis designed for analyzing coordinate-based data showing the brain regions activated for specific behaviors. ALE provides combined images that show not only the activated brain regions, but also important regions activated for the combination among behaviors. For the purpose of this study, the target brain areas are associated with each of the emotions of interest (fear, happiness, sadness, surprise, disgust, and anger) and consumer decision-making. Existing studies including the target behaviors were collected according to the principles of the PRISMA statement. Details about collecting and analyzing data will be presented in the results part of this study.

Brain Connectivity (Study 2)

For one of the purposes of this study, brain mapping based on the neural interaction, or functional connectivity between emotions and cognitions, social network theory is employed.

Artificial Intelligence (AI) has become a widely used method to investigate patterns of big data and estimate a result through such as regression-based or classification-based specific algorithms. Mathematical applications and computer programs use machine learning algorithms to explore and solve a problem with data (Alpaydin, 2010). There have been many successful applications of machine learning including systems that analyze past sales to predict consumer behaviors, optimize robot behaviors so that a task can be completed using minimum resources, and extract knowledge from bioinformatics data. For instance, Google and Amazon collect their customers' information and data through their Internet-based business platforms and attempt to find a pattern for each consumer's behavior and preference and help improve value for both company and customers.

This approach using machine learning as a tool for analyzing data efficiently and finding a solution for a specific research question has evolved in the fields of neuroimaging analysis and business disciplines. In this research, machine learning is used to find patterns of behavioral and neural data. In particular, this study uses a big size of data about brain activity for specific behaviors, demographic information, and metabolic information. Thus, this study requires a machine learning approach to deal with the big image and meta data.

Connectivity shows a pattern of brain activity by showing the level of interaction and its strength. Furthermore, it can show a pattern of connectivity of the linkage between nodes (region of interest: ROI) and edges (other brain regions neighboring the regions of interest). A machine learning algorithm is useful to find connectivity among brain regions because it is able to show the changes and the pattern of brain activity to behaviors and thus to illustrate how the brain works for behaviors, physiologically and behaviorally. Many statistical and mathematical applications have been used in neural connectivity studies. GraphVar 2.0 (GV2) is a newer way

of investigating the connectivity between neural functions in the human brain and graphing brain functional connectivity based on the strength of each connection between brain regions activated for specific behaviors (Kruschwitz, List, Waller, Rubinov, & Walter, 2015). It is operated in a Matlab-based environment, so it is important to understand the mathematical and logical functions used to develop the program. Statistical Parametric Mapping (SPM) is a collection of open-source Matlab scripts and the most popular software for the analysis of fMRI data. It has several methods of displaying the results and data visualization for single-subject and multiple-subject studies.

There are also many different methods for investigating brain connectivity, including the brain connectivity toolbox (Rubinov & Sporns, 2010), eConnectome (He et al., 2011), GAT (Hosseini, Hoefl, & Kesler, 2012), CONN (Whitfield-Gabrieli & Nieto-Castanon, 2012), BASCO (Gottlich et al., 2015), GRETNA (Wang et al., 2015), BRAPH (Liao et al., 2014), and BSMART (Cui, Xu, Bressler, Ding, & Liang, 2008). These methods all allow dynamic connectivity analyses. However, as noted above, data size has increased dramatically due to advances in the experimental capacity in fMRI such as involving more participants and dynamic experimental designs (Waller et al., 2018). Therefore, connectivity analysis must deal efficiently and effectively with a big size of data.

All of these graphical approaches have been developed based on the theory of social network (hereafter SNT). According to Kruschwitz et al., (2015) and Waller et al. (2018), studying a neural connectivity using large datasets is important to provide insightful suggestions about various methods for different purposes of neuroimaging and connectivity studies, building a prediction model, selecting a prediction gadget and features based on user-friendly environment in terms of no-coding process, regularization method which is an important

algorithm for classification or regression, model selection and validation, cross-validation, nested cross-validation, and model performance for parametric and non-parametric testing. Thus, based on these contributions and functional utility, this study employs several applications developed with SNT as tools to analyze brain functional connectivity. The list of applications employed for this study is presented in Table 5.

Table 5. Methods for Study 1 and Study 2

Applications	Study	Purpose	Versions
MATLAB	Study 2	Data analysis and management	2018 (a)
MAPLE 18	Study 2	Visualization	2018
NetMiner	Study 2	Neural connectivity	2.0.1
Mango	Study 1 & 2	Visualization	4.0
GingerALE	Study 1	Meta-analysis (MNI coordinates)	2.3.6

CHAPTER IV

ANALYSIS AND RESULTS

This research had two pilot studies. Pilot Study 1 (PS1) tested an interaction between brain activity for two important behaviors (language formation as a proxy of cognition and happiness as a proxy of emotions) through ALE meta-analysis. Pilot Study 2 (PS2) tested the validation and rationality of HCP archival fMRI data by drawing a brain map based on [x, y, z] coordinates for emotional brain activity. To convert image data into numerical information, PS2 employed MATLAB and R software with coding process. After verifying that the results of PS1 and PS2 supported the purpose of this research, two main studies were conducted: Study 1 (ST1) used PRISMA statement and ALE meta-analysis to seek an association among brain activity for all emotional and cognitive behaviors including fear, sadness, happiness, disgust, surprise, anger, and consumer decision-making. Study 2 (ST2) employed several statistical methods to develop and visualize brain functional connectivity based on the findings of ST1 and HCP archival fMRI data.

Pilot Study 1

Study Selection

The first pilot study aimed to find a connection between emotion (happiness) and cognition (language) through a coordinate-based meta-analysis using the activation likelihood estimation (ALE) method (Eickhoff et al., 2009; Eickhoff et al., 2012; Turkeltaub et al., 2002).

Results from neuroimaging studies featuring experiments on happiness (positive) emotion and cognition (language only) were included. The following inclusion criteria were used to select the studies: (a) studies in peer-reviewed journals published in English, (b) use of fMRI neuroimaging technique, (c) studies featuring keywords “fMRI” or “functional magnetic resonance”, “happiness” or “positive affect”, and “language” or “linguistic cognition”, (d) studies providing or reporting $[x, y, z]$ coordinates for happiness as an emotion and language as a cognitive behavior, and (e) to avoid bias, we excluded studies using anatomical or neural interaction between emotion and language. In total, 13 fMRI studies (total number of foci = 98, total number of participants = 225) were included in the final meta-analysis as shown in Table 6. Foci that were located outside the mask of gray matter by GingerALE 2.3.6 were excluded from all investigations.

ALE analysis

To investigate which brain regions were implicated in happiness and language, we employed the ALE meta-analytic method (Turkeltaub et al., 2002; Eickhoff et al., 2009) using GingerALE (<http://brainmap.org/ale/index>). There are several advantages to using this method: (a) it provides a quantitative and objective measure of the convergence of neuroimaging findings; thus it identifies the activated brain region, (b) this identification empirically supports what studies are looking for, and (c) it finds gaps among studies. The ALE method extracts three-dimensional (Talairach or MNI) activation foci from relevant selected studies. These peak activation coordinates are displayed as a three-dimensional Gaussian distribution with an estimated full-width half maximization (FWHM) based on the selected studies. Probability distributions from an experiment are merged into a modelled activation (MA) map. Each MA

map is combined into an ALE map on a voxel by voxel basis (Turkeltaub et al., 2012). The ALE map reflects the combined activation patterns of all experiments involved in the meta-analysis. To control for multiple comparisons, the ALE map was thresholded at a false discovery rate (FDR) of $p < 0.001$, uncorrected. This study used a slightly more conservative cluster size threshold of 200 mm^3 than other ALE studies that have 100 mm^3 as a threshold (Cromheeke & Mueller, 2014). Lastly, ALE maps were overlaid onto anatomical T1 weighted images in Talairach space and displayed with Mango software (<http://www.ric.uthscsa.edu/mango>).

Table 6. fMRI Studies Included in the Meta-analysis (PS1)

	First Author	Year	Sex (F/M)	Template	System	Threshold	Analysis
1	Acevedo	2014	10/8	MNI	3T	$p < 0.001$	SPM
2	Banks	2007	8/6	MNI	1.5T	$p < 0.001$	SPM
3	Berl	2014	26/31	MNI	3T	$p < 0.05$	SPM
4	Blair	2007	12/10	MNI	1.5T	$p < 0.005$	AFNI
5	Johnstone	2006	20/20	MNI	3T	$p < 0.05$	AFNI
6	Koelsch	2006	5/6	MNI	3T	$p < 0.005$	LIPSIA
7	McRae	2008	10/12	MNI	3T	$p < 0.001$	SPM
8	Nummenmaa	2008	10/0	MNI	1.5T	$p < 0.001$	SPM
9	Ochsner	2002	15/0	MNI	3T	$p < 0.001$	SPM
10	Pereira	2011	5/9	MNI	1.5T	$p < 0.005$	FEAT/FSL
11	Tie	2014	8/6	MNI	3T	$p < 0.001$	SPM
12	Tu	2015	45	MNI	1.5T	$p < 0.05$	SPM
13	Viinikainen	2010	9/8	MNI	3T	$p < 0.001$	BrainVoyager

Emotion (positive and/or happy)

The main ALE analysis of emotion revealed eight significant clusters, as shown in Table 7 with the largest cluster (volume = 7504 mm^3) located in the left medial and superior frontal gyrus. The maximum ALE value of 3.79 was also observed in the left superior frontal gyrus (SFG: cluster volume = 7504 mm^3). Other significant clusters included the right insula, cingulate gyrus, the left middle temporal gyrus, and the right middle frontal gyrus. These findings about emotion regulation empirically support the findings of previous studies selected

for the test as shown in Table 6. This is remarkable because the left inferior frontal gyrus is usually thought to control language (Vigneau et al., 2006), but PS1 found it was activated for emotions (cluster volume = 1080 mm^3) because the left inferior frontal gyrus is generally known as the region (BA 44 and 45) that controls the process of generating language (Rizzolatti & Arbib, 1998).

Table 7. ALE Activation Clusters Associated with Emotion (Happiness)

Cluster	L/R	Anatomical label	BA	Volume (mm^3)	ALE value ($\times 10^{-3}$)	Peak coordinates			N studies (foci)
						x	y	z	
1	L	Superior Frontal Gyrus	6	7504	3.79	-14	22	56	8(8)
		Medial Frontal Gyrus			3.34	-2	10	54	
2	R	Insula	13	1320	2.73	38	24	2	3(3)
		Inferior Frontal Gyrus			2.65	44	26	4	
3	R	Cingulate Gyrus	32	1208	2.64	6	24	42	2(3)
			24		2.63	8	14	32	
4	L	Inferior Frontal Gyrus	44	1080	2.76	-52	16	14	2(2)
5	L	Clastrum		648	2.67	-28	20	4	3(3)
6	L	Middle Temporal Gyrus	21	320	2.53	-60	-38	-4	1(1)
7	R	Middle Frontal Gyrus	10	312	2.53	36	46	4	1(1)
8	R	Caudate		208	2.52	14	8	22	2(2)

N: number of studies reporting at least one activation peak; Coordinates: MNI; Space = mm^3 , cubic millimeter, BA: Brodmann Area

Cognition (language formation)

The meta-analysis of cognition supports the existing literature that the language formulation area in the brain is located in the inferior frontal gyrus (Homae et al., 2002). The main ALE analysis of cognition reported four significant clusters, as shown in Table 8, with the largest cluster (volume = 2912 mm^3) located in the left inferior frontal gyrus and precentral gyrus. The maximum ALE value of 1.87 was observed in the right middle frontal gyrus (cluster volume = 1920 mm^3). Other clusters are included in the left inferior frontal gyrus and the right caudate. The most significant cluster was localized in the left inferior frontal gyrus and precentral gyrus. This finding is important because this area is also partially responsible for

empathy and for processing pleasant and unpleasant emotional scenes (Farrow et al., 2001; Lane et al., 1997).

Table 8. ALE Activation Clusters Associated with Cognition (Language)

Cluster	L/R	Anatomical label	BA	Volume (mm^3)	ALE value ($\times 10^{-3}$)	Peak coordinates			N studies (foci)
						x	y	z	
1	L	Inferior Frontal Gyrus	9	2912	1.84	-44	14	28	2(4)
		Precentral Gyrus	9		1.73	-44	10	32	
2	R	Middle Frontal Gyrus	46	1920	1.87	50	22	24	2(3)
3	L	Inferior Frontal Gyrus	45	1736	1.65	-52	18	-2	2(3)
			45		1.50	-50	24	4	
4	R	Caudate		936	1.58	14	10	10	2(2)

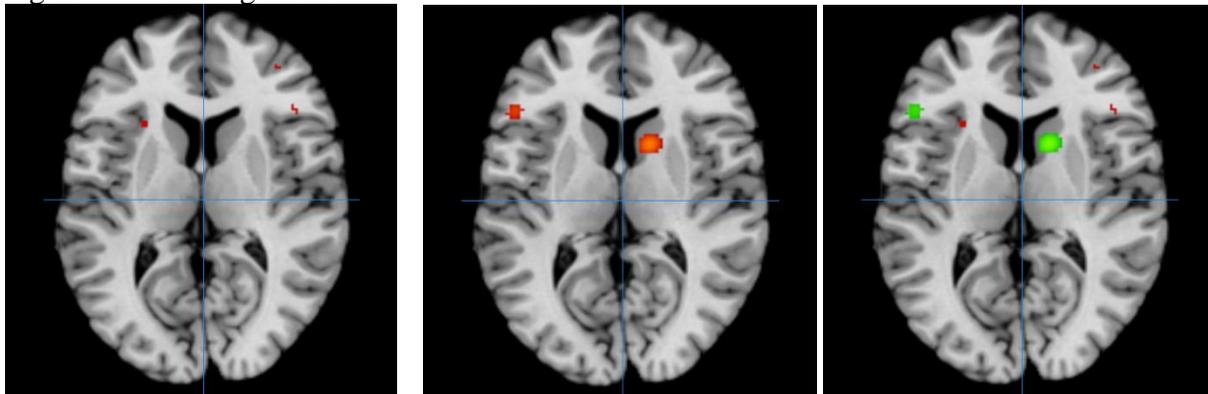
N: number of studies reporting at least one activation peak; Coordinates: MNI; Space = mm^3 , cubic millimeter, BA: Brodmann Area

In summary, this meta-analysis (PS1) sought to find consistencies among an increasing number of studies investigating a cognitive behavior (language). The results are helpful to model the neural interaction between cognition and emotion. While cognition (language) is regulated in the left inferior frontal gyrus, the right middle frontal gyrus, and left inferior frontal gyrus, emotion is mostly localized in the left superior and medial frontal gyrus. However, interestingly, the left inferior frontal gyrus, which is known to house the function that controls formulating language, is strongly associated with happiness (volume = $1080 mm^3$, the fourth largest brain region for the emotion). Based on these findings, we can argue that there is a significant neural interaction between brain regions for each of emotion and language as shown in Figure 5. Thus, it is important for studies on consumer decision-making to understand that consumers are using both emotion (happiness) and cognition (language) when they behave for each of happiness and language.

With this point of view, PS1 argues that there are neurological and behavioral evidence that neural interactions between emotion and cognition exist in the brain. Thus, as shown in the results that creating words as a cognitive behavior links to positive (or happy) emotion as an

emotional behavior, this study concludes that further studies need to support consumers can be considered not only as thinkers, but also as feelers. This argument challenges the previous research used primary perspectives in consumer research and aims to change to alternative perspective with neuroscientific evidence. Therefore, the research would have a theoretical contribution by suggesting the new point of view, which is an integrated or alternative perspective that individuals coincidentally utilize their cognitive abilities and emotional abilities when they make a decision, in the stream of research on consumer decision-making process.

Figure 4. Brain Regions for Each Behavior in PS1



Note: The left panel shows the ALE foci for happiness (positive emotion). The middle panel shows the ALE foci for language (cognition). The right panel shows the ALE foci for both happiness and language.

Pilot Study 2

Small samples (500 subjects' brain images from HCP) were employed for Pilot Study 2 (PS2), which attempted to verify the validity and accuracy of human brain images from HCP data by using the data of 500 subjects' brain images to draw a brain map based on brain regions activated for emotional behaviors. The sample data only included the left and right accumbens, the left and right amygdala, brain stem, the left and right caudate, the left and right cerebellum, the left and right diencephalon ventral, the left and right hippocampus, the left and right pallidum, the left and right putamen, and the left and right thalamus as shown in Table 9. The

brain images consist of three-dimensional coordinates [x, y, z]. Each point in the coordinates indicates a highly activated point in the human brain.

Table 9. Brain Regions for Emotional Behaviors Identified with Colors

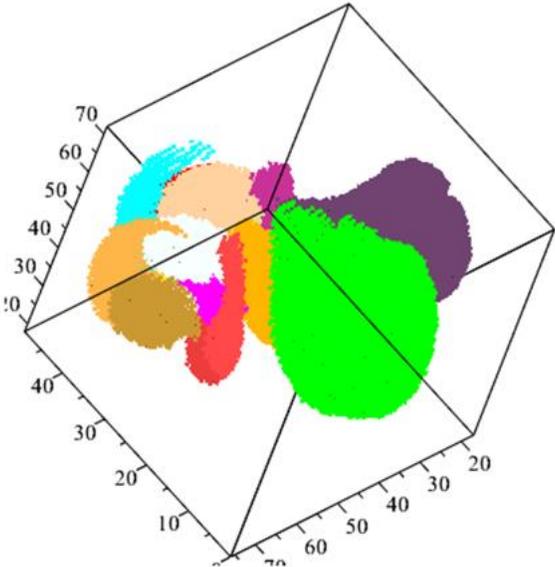
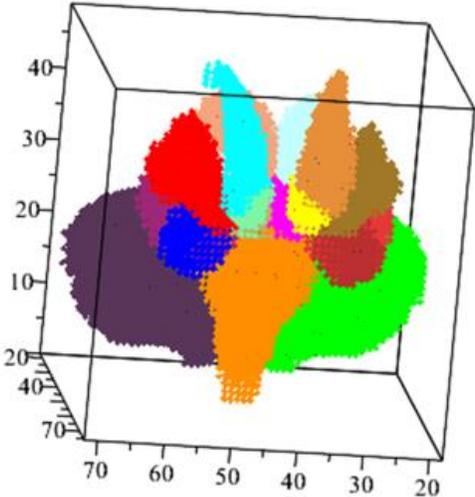
Anatomical Brain Regions	Colors	Anatomical Brain Regions	Colors
ACCUMBENS_LEFT	Aquamarine	DIENCEPHALON_VENTRAL_RIGHT	Magenta
ACCUMBENS_RIGHT	Yellow	HIPPOCAMPUS_LEFT	Maroon
AMYGDALA_LEFT	Blue	HIPPOCAMPUS_RIGHT	Orange
AMYGDALA_RIGHT	Brown	PALLIDUM_LEFT	Pink
BRAIN_STEM	Coral	PALLIDUM_RIGHT	Plum
CAUDATE_LEFT	Cyan	PUTAMEN_LEFT	Red
CAUDATE_RIGHT	Gold	PUTAMEN_RIGHT	Sienna
CEREBELLUM_LEFT	Violet	THALAMUS_LEFT	Tan
CEREBELLUM_RIGHT	Green	THALAMUS_RIGHT	Turquoise
DIENCEPHALON_VENTRAL_LEFT	Khaki		

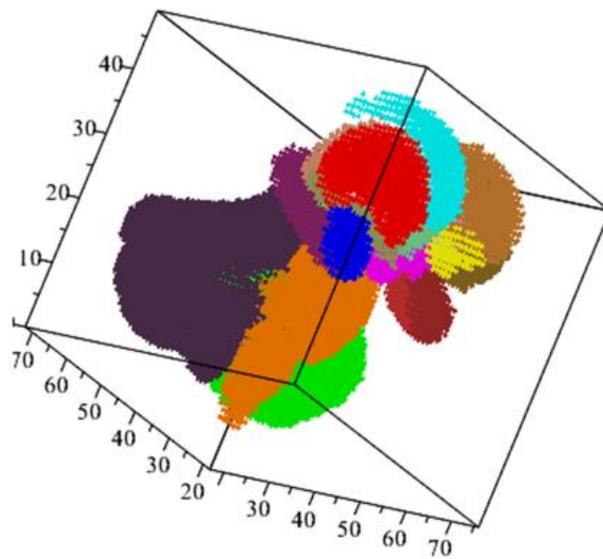
Other studies using the data have shown the rationality and the accuracy of the data. Van Essen et al. (2012) and Van Essen et al. (2013) explained how to collect and process the data from unprocessed raw data to processed data to make it valid and practical. Mars et al. (2018) argued that the data from HCP can be used for brain studies and pointed out its relevance and value through comparing with different datasets from other institutes because they found using HCP1 data as well as using other datasets is valuable and meaningful for neuroscience research to contribute to increasing the understanding of brain connectivity. Finn et al. (2015) also supported the rationality and accuracy of the HCP brain image data by suggesting possible research agendas including brain mapping of population-level inferences and functional connectivity of each individual's networks.

To conduct PS2, I collected the coordinates from each brain image through a process of transforming image data into numerical information in the coordinate system. PS2 employed MATLAB and R software with coding process to transfer image data into numerical data in the coordinate system. To display a product, which is a brain map from the coordinate information of each individual's brain image, PS2 employed mathematical software (MAPLE) with coding process based on graph theory to draw a 3D brain image (Wagner et al., 2001; Zaim et al., 2007). The result of PS2 that verifies the rationality and accuracy of the data and draws a brain map using 500 subjects' brain images is presented in Figure 6.

Based the result of PS2, Study 2 in the research would have support the association among brain activity for both emotions and consumer decision-making by visualizing the association in the brain map using coordinate-based analysis. It would also provide initial physiological and behavioral findings that show brain connectivity, which is about the functional neural networks, among the brain activity for emotional and cognitive behaviors. To summarize the pilot studies, PS1 explored and verified an association between cognitive behavior (language formation) and emotional behavior (happiness) by investigating brain activity for each of the two behaviors. The results of PS2 indicate that the HCP data sets are valid for neuroimaging studies, especially seeking a pattern of brain activity and its connectivity based on behaviors such as emotions and cognitions. The data have good quality and validation in data processing (Van Essen et al., 2012; Van Essen et al., 2013).

Figure 5. Screen Captures of 3D Draft Brain Mapping (Emotions)





Note: The upper map is for the front side of the brain, the middle map is for the left side of the brain, and the bottom map is for the right side of the brain.

Study 1 (Association between Emotions and Consumer Decision-making)

The purpose of Study 1 (ST1) is to find interactions of emotions when consumers make a decision through analyzing neural activity for each of the six identified emotions and consumer decision-making. To support the associated neural activity with scientific evidence, ST1 employed ALE meta-analysis, a popular method in the neuroscience discipline (Eickhoff et al., 2012; Stocco, 2014). For ST1, I used the principles of the PRISMA statement to increase the validity and credibility of the meta-analysis by systematically collecting previous research on both emotional and cognitive behaviors in consumer research and neuroscience research. Then, with the criteria for selecting studies fitted to the purpose of ST1, I collected 66 studies after the entire process of PRISMA statement as presented in Figure 3.

The results of PS1 verified that there is an interaction between emotional behavior (happiness as a proxy of emotions) and cognitive behavior (language formation as a proxy of cognitions). This finding supports the theoretical argument that cognitive behaviors and

emotional behaviors are correlated or associated with each other even if each of regions activates for each behavior. To empirically support the theoretical assumption that consumers' decision-making process consists of interactions between cognitive behaviors and emotions, ST1 extended PS1, which only looked at happiness as a proxy of emotions, to include the emotions (i.e., happiness, sadness, disgust, fear, anger, and surprise) suggested by Barrett (2017), Gasquoine (2016), Mowen and Minor, (1998), Poldrack et al. (2006 & 2011), and Reed (2013).

Consumer Decision-Making

Results of the meta-analysis of consumer decision-making supports the previous and existing studies (Table 4) that when consumers make a decision or purchase a product or brand, different neural areas activate in the brain such as the orbitofrontal cortex (OFC), dorsolateral prefrontal cortex (dlPFC), anterior cingulate cortex (ACC), ventromedial prefrontal cortex (vmPFC), insula, medial prefrontal cortex (mPFC), and nucleus accumbens (NAcc).

Table 10. fMRI Studies of Consumer Decision-making

#	First author	Year	Subjects	Template	Threshold	Analysis
1	Bradley	2015	46	MNI	$p < .001$	SPM
2	Bray	2008	23	MNI	$p < .001$	SPM
3	Carmell	2014	19	MNI	$p < .001$	SPM
4	Casaratto	2012	15	MNI	$p < .01$	SPM
5	Creswell	2013	33	MNI	$p < .001$	SPM
6	De Martino	2017	22	MNI	$p < .001$	SPM
7	Deppe	2005	22	MNI	$p < .01$	SPM
8	Huijsmans	2018	47	MNI	$p < .001$	SPM
9	Jung	2018	42	MNI	$p < .05$	SPM
10	Kang	2013	27	MNI	$p < .001$	SPM
11	Knutson	2017	26	MNI	$p < .001$	SPM
12	McClure	2004	67	MNI	$p < .05$	SPM
13	Owens	2017	1113	MNI	$p < .001$	SPM
14	Tschue	2010	17	MNI	$p < .001$	SPM
15	Van der Laan	2012	20	MNI	$p < .001$	SPM

16	Waskow	2016	25	MNI	$p < .001$	SPM
17	Berns	2012	32	MNI	$p < .001$	SPM
18	Schaefer	2006	13	MNI	$p < .001$	SPM
19	Klucharev	2008	24	MNI	$p < .001$	SPM
20	Plassmann	2007	19	MNI	$p < .001$	SPM
21	Esch	2012	20	MNI	$p < .001$	SPM

Note: subjects = a number of participants (only healthy adults), MNI = Montreal Neurological Institute

ALE meta-analysis of consumer decision-making reported findings of brain regions activated for consumer decision-making as a cognitive behavior as presented in Table 11. To be more conservative for this study, the threshold point was set with the minimum volume size of 200 mm^3 and FDR p was .001 as Eickhoff et al. (2009) and Eickhoff et al. (2012) suggested. ALE analysis on consumer decision-making resulted in 13 clusters based on the threshold points. The total number of foci is 360, and 21 experimental studies were selected for ST1 as shown in Table 10 and 11. The MNI system was the only coordinate system used for this study because of increasing the accuracy of selecting studies. The total number of voxels in ST1 was 264,007, and each voxel was measured with $1*1*1 \text{ mm}$. A total of 1672 subjects participated in all selected studies. One of selected has 1113 participants to investigate brain regions for measuring decision-making. To calculate the FWHM that is a function of the difference between two extreme values of the independent variable where the dependent variable is equal to half of its maximum value (Eickhoff et al., 2009), ALE analysis needs subject information for each foci group to calculate FWHM of the Gaussian function used to blur the foci. The range of FWHM values in ALE analysis for this study was from 8.4269 to 9.1081. The largest cluster (volume = 1952 mm^3) was located in the anterior cingulate cortex, which mainly activates for specific cognitive behaviors including attention, reward anticipation, and decision-making (Pardo et al., 1990). The next largest cluster of foci (volume = 1544 mm^3) is in the caudate nucleus, which activated for goal-directed action (Grahn et al., 2009) and different cognitive behaviors including

memory, learning, and language (Hannan et al., 2010). The ALE values of each brain region are reported in Table 11.

The brain regions for consumer decision-making include the medial frontal gyrus, dorsolateral prefrontal cortex, inferior frontal gyrus (known as the Broca area) activated for language formation, and superior temporal gyrus (known as the Wernicke area) activated for interpreting and understanding the meaning of language. This finding supports the literature reviewed in this study that shows the prefrontal and temporal cortices activated for consumer decision-making. The result of ALE analysis of brain regions for consumer decision-making shows that a brain region activated for emotions was presented such as amygdala (9th largest cluster, 408 mm^3 , ALE value .0212, $p < .001$ at z-value 4.45).

Table 11. ALE Activation Clusters Associated with Consumer Decision-Making

#	x	y	z	ALE Value	p-value	z-score	BA	Neuroanatomical Label
1	-4	40	-10	0.023662	7.33E-07	4.815879	24	Anterior Cingulate
	-4	58	-2	0.019142	1.60E-05	4.159098	10	Medial Frontal Gyrus
	4	46	-6	0.019082	1.66E-05	4.150220	32	Anterior Cingulate
	-4	34	-18	0.016729	7.47E-05	3.792147	32	Anterior Cingulate
2	-12	10	0	0.026074	1.34E-07	5.145001		Caudate
	-10	10	8	0.019866	9.93E-06	4.266487		Caudate
	-8	0	0	0.013432	6.16E-04	3.231252		Lentiform Nucleus
3	-14	56	24	0.021475	3.36E-06	4.502074	9	Superior Frontal Gyrus
4	-40	6	30	0.019004	1.75E-05	4.138436	6	Precentral Gyrus
5	-50	26	16	0.020849	5.17E-06	4.409924	45	Inferior Frontal Gyrus
6	12	12	-2	0.017275	5.25E-05	3.878731		Caudate
	8	4	-8	0.015836	1.33E-04	3.645854	25	Anterior Cingulate
7	-4	44	10	0.022669	1.47E-06	4.674805	32	Anterior Cingulate
8	-2	30	32	0.016466	8.83E-05	3.750399	32	Cingulate Gyrus
	-6	34	38	0.01553	1.63E-04	3.593732	8	Medial Frontal Gyrus
9	-20	-4	-16	0.021151	4.22E-06	4.453831		Amygdala
10	18	0	-12	0.016003	1.20E-04	3.672806		Lentiform Nucleus
11	10	54	20	0.018142	3.04E-05	4.010051	9	Medial Frontal Gyrus
12	58	-42	20	0.014621	2.95E-04	3.435915	13	Superior Temporal Gyrus.
	58	-38	30	0.014097	4.09E-04	3.346402	40	Inferior Parietal Lobe
13	-42	-86	-4	0.015432	1.74E-04	3.577018	19	Inferior Occipital Gyrus

	-44	-82	2	0.015172	2.06E-04	3.532447	19	Inferior Occipital Gyrus
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Note: BA: Brodmann area, Volume: cubic millimeter (mm^3) = a voxel, peak coordinates = MNI, $p^* < .001$

Emotions: happiness, sadness, angry, fear, surprise, and disgust

Existing studies on emotions found and reported neurological information that shows activated brain regions for emotional behaviors including affective categories suggested by Barrett (2017), Ekman (1972), and Gasquoine (2016): happiness, sadness, anger, fear, surprise, and disgust. ALE meta-analysis was conducted to summarize the findings of previous studies and investigate new findings about the neural regions activated for emotional behaviors.

Literature in emotions showed that the amygdala, cerebellum anterior lobe, caudate, hippocampus, thalamus, posterior insula, and putamen responds to emotional behaviors.

Table 12. fMRI Studies of Emotional Behaviors

#	First author	Year	Subjects	Template	Threshold	Analysis
Anger						
1	Alia-Klein	2018	37	MNI	$p < .005$	SPM
2	Capitão	2019	31	MNI	$p < .01$	SPM
3	Heesink	2018	30	MNI	$p < .001$	SPM
4	Kim	2019	220	MNI	$p < .001$	SPM
5	Baudes-Rotger	2017	36	MNI	$p < .01$	SPM
6	Gilam	2018	25	MNI	$p < .05$	SPM
7	Jiang	2018	39	MNI	$p < .001$	SPM
8	Hornung	2019	16	MNI	$p < .001$	SPM
Disgust						
9	Schienze	2002	12	MNI	$p < .001$	SPM
10	Hofler	2018	29	MNI	$p < .001$	SPM
11	Oaten	2018	22	MNI	$p < .005$	SPM
12	Schienze	2018	38	MNI	$p < .001$	SPM
13	Wabnegger	2018	49	MNI	$p < .001$	SPM
14	Ying	2018	36	MNI	$p < .05$	SPM
15	Lim	2017	19	MNI	$p < .05$	SPM
Fear						
16	Benuzzi	2004	13	MNI	$p < .01$	SPM
17	Yurgelun-Todd	2006	16	MNI	$p < .001$	SPM

18	Milad	2007	17	MNI	$p < .005$	SPM
19	Merz	2010	48	MNI	$p < .001$	SPM
20	Lissek	2014	20	MNI	$p < .005$	SPM
21	Williams	2001	11	MNI	$p < .001$	SPM
22	Armony	2002	10	MNI	$p < .01$	SPM
23	Brugger	2011	21	MNI	$p < .005$	SPM
Happiness						
24	Johnstone	2006	40	MNI	$p < .001$	SPM
25	Fujiwara	2013	18	MNI	$p < .001$	SPM
26	Winecoff	2013	31	MNI	$p < .01$	SPM
27	Dalenberg	2017	45	MNI	$p < .001$	SPM
28	Habel	2005	26	MNI	$p < .001$	SPM
29	Park	2017	50	MNI	$p < .001$	SPM
30	Matsunaga	2016	26	MNI	$p < .01$	SPM
31	Shany	2019	40	MNI	$p < .001$	SPM
Surprise						
32	Kanwisher	1997	20	MNI	$p < .05$	SPM
33	Bartolo	2006	21	MNI	$p < .01$	SPM
34	Egner	2010	16	MNI	$p < .001$	SPM
35	Vrticka	2014	20	MNI	$p < .001$	SPM
36	Murty	2016	53	MNI	$p < .001$	SPM
37	Wessel	2012	19	MNI	$p < .001$	SPM
Sadness						
38	Yoshino	2010	15	MNI	$p < .005$	SPM
39	Khalfa	2005	13	MNI	$p < .01$	SPM
40	Barrett	2004	14	MNI	$p < .001$	SPM
41	Habel	2005	26	MNI	$p < .001$	SPM
42	Bogert	2016	63	MNI	$p < .001$	SPM
43	Mel'nikov	2018	21	MNI	$p < .001$	SPM
44	Park	2015	24	MNI	$p < .05$	SPM
45	Ramirez-Mahaluf	2018	22	MNI	$p < .05$	SPM

Note: subjects = a number of participants (only healthy adults), MNI = Montreal Neurological Institute

ST1 collected 45 studies providing MNI and investigating a role of emotions in the process of decision-making. To find commonly and uniquely activated neuroanatomical locations, ST1 conducted the meta-analysis of emotions. In general statistic, there were total 264,227 voxels with 814 foci in 45 studies piled up for this investigation. As suggestions of

conducting ALE analysis in a study of Eickhoff et al. (2012), this investigation used the selected 45 studies. FWHM range was from 8.4900 to 10.0025 and the range of ALE value was from .000 to .065. The results of meta-analysis show that the largest activated brain area was the left and right amygdala with the first (4224 mm^3) and second largest (2912 mm^3) clusters of foci, respectively. The third largest volume of the activated neural region for emotions was 768 mm^3 in the anterior cingulate cortex (ACC). Thus, this investigation empirically supported the findings of the literature review that amygdala and anterior cingulate cortex (ACC) are activated when consumers feel an emotion. All brain regions activated for emotions in this investigation are presented in Table 13.

The fourth and eighth largest areas (volume size = 768 mm^3 and 248 mm^3) are located in the fusiform activated for recognition as a cognitive behavior (Hubbard & Ramachandran, 2005). The fourth largest area (volume size = 440 mm^3) is located in the anterior cingulate cortex (ACC). This anatomical area activates for decision-making (Bush et al., 2002) as well as emotions (Decety & Jackson, 2004). The seventh largest area (volume size = 296 mm^3) is located in the middle temporal gyrus, known as a brain function that is activated for recognition and accessing word meaning in reading (Wernicke's area). This study collected a few of existing studies with the very specific selection criteria, but the result of ALE analysis interestingly sufficiently shows that brain regions for cognitive behaviors were coincidentally activated for emotions when consumers made a decision. All results of the ALE analysis are presented in Table 13 as below.

Table 13. ALE Activation Clusters Associated with Emotions

#	x	y	z	ALE Value	p-value	z-score	BA	Neuroanatomical Label
1	-20	-4	-16	0.064664	7.15E-18	8.533328		Amygdala
2	24	-2	-18	0.049296	1.14E-12	7.016325		Parahippocampal gyrus
3	-4	32	18	0.026783	4.05E-06	4.462758	24	Anterior Cingulate

4	-36	-48	-18	0.025153	1.05E-05	4.25358	37	Fusiform Gyrus
5	0	-52	28	0.025285	9.76E-06	4.270424	31	Cingulate Gyrus
6	34	-58	-14	0.025499	8.58E-06	4.298883		Posterior Lobe.
7	-46	-60	14	0.021898	6.72E-05	3.81838	39	Middle Temporal Gyrus
8	40	-74	-8	0.021159	1.01E-04	3.716124	19	Fusiform Gyrus
9	14	14	-10	0.023017	3.58E-05	3.971089		Caudate

In addition, the results of ALE analysis include different brain regions which are not directly related to emotional behaviors, such as the fusiform gyrus activated for recognition memory processing (Haeger et al., 2018) and middle temporal gyrus activated for recognition and word processing (Papeo et al., 2019). For this investigation, ST1 only collected previous studies decision-making and emotions. Especially, in collecting studies for emotions, this study collected only studies of emotions in processing information (advertisement) for decision-making. Thus, it leads to identifying brain regions for emotions in the information process of consumer decision-making.

Results of neural regions by ALE analyses for decision-making and emotions (Study 1)

Through ALE meta-analysis, ST1 verified the brain regions activated for both emotions and consumer decision-making. Only studies related to consumer decision-making as a cognitive behavior and emotions were collected for this analysis. Each selected study of emotions was related to consumer decision-making. Thus, it helped to sufficiently understand the role and effect of emotions in the information process of consumer decision-making. As the results show (Table 11), several brain regions are commonly activated for consumer decision-making, such as anterior cingulate cortex (ACC), caudate, superior frontal gyrus, precentral gyrus, and inferior temporal gyrus. However, there is a different pattern of brain regions activated for the behavior of consumer decision-making. For instance, ACC (the largest volume) and the amygdala (the 9th

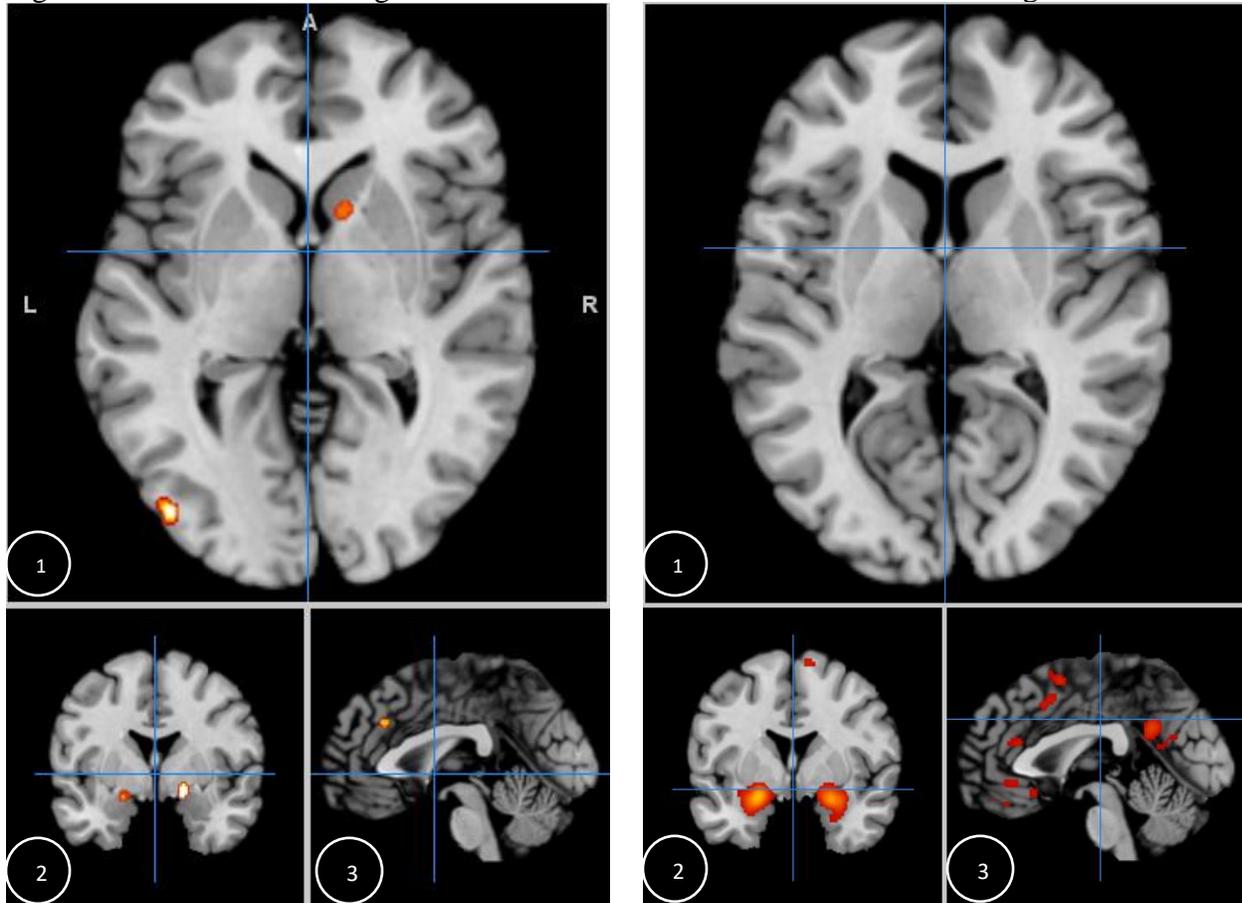
largest of all the clusters of brain regions) activated for the consumer decision-making. Both ACC and the amygdala have been traditionally known as the brain region activated mainly for emotions. This study has a different result that ACC and the amygdala were activated for consumer decision-making from previous studies on the brain regions: ACC and the amygdala.

In the investigation of brain regions activated for emotions, most of the clusters that activated for emotions (e.g., ACC and amygdala) were similar to the findings in the previous literature used for this meta-analysis. Findings of this study support the argument that emotions actively participate in the process of consumer decision-making about purchasing a product/brand or choosing among products/brands. In the analysis of the group of studies on consumer decision-making, the largest activated neural area for consumer decision-making was the anterior cingulate cortex (ACC). It has performed to control emotional behaviors such as regulating emotions (Szekely et al., 2017). This study found that the amygdala which is one of the largest activated areas for the behavior of consumer decision-making was activated (volume size = 408 mm^3). The neural area mainly works for emotional behaviors.

On the other hand, in the analysis of the group of studies on emotional behaviors, one of the largest associated areas for emotional behaviors was located in the parahippocampal gyrus, which mostly works for the cognitive behavior of memory. According to Lighthall, Huettel, and Cabeza (2014), consumers use their memory to compare and decide about a product in terms of willingness to pay (WTP), especially in online shopping environments. Also, fusiform gyrus activated for emotions. The area mainly works for cognition, which is recognition (Haeger et al., 2018). The graphical results were created through using Mango software (<http://ric.uthscsa.edu/mango/>) support the argument that brain regions activated for cognitions will

be associated with brain regions for emotions, and vice versa. The results are presented in Figure 6.

Figure 6. Activated Brain Regions for Emotions and Consumer Decision-making



Note: Left side shows clusters of brain regions activated for consumer decision-making. Right side shows clusters of brain regions activated for emotional behaviors with the same stimuli (pictures and written messages) in ALE analysis of cognitive behaviors. The largest picture in the upper side (1) indicates z-axis (changes in the height of a neural location), the left side in the bottom (2) indicates y-axis, and the right side in the bottom (3) indicates x-axis.

Study 2 (Brain Functional Connectivity)

Study 2 (ST2) aims to identify common activated neural areas for emotions and consumer decision-making and map a neural connectivity among the areas to answer a neurological research question rather than a behavioral research question like Study 1 (ST1). This question is, how different neural areas are physiologically connected to each other to implement a behavior. Thus, ST2 looks for the patterns of connectivity among neural activated

areas for both consumer decision-making and emotions. By mapping the connectivity based on the neurological and physiological findings of ST1 and analyzing fMRI data of both consumer decision-making and emotions, ST2 seeks a way to answer the research question, mapping consumer cognition and emotions for consumer decision-making. For this purpose, ST2 used a specific statistical tool based on social network theory (SNT) to draw the neural connectivity of the brain regions (consisting of nodes and edges) activated for decision-making and emotions in the information process by matching neural regions (edges) from ST1 with brain regions (nodes) identified in analyzing HCP fMRI image data.

For ST2, 1108 subjects' brain images from HCP were used to mathematically and neurologically verify the brain regions by pulling out the coordinate information of each brain region and visualizing it with different statistical software such as MAPLE, MATLAB, and R. T1w images of each participant in each task were used to obtain MNI coordinates by taking FSL's FNIRT algorithm of a non-linear optimization procedure that aims to minimize the sum of squared differences between two images by Glasser et al. (2016). Extracted MNI coordinate information of each neural activation was used to draw a mask of brain map as a foundation of the map (nodes). After that task, this study used network analysis (based on SNT) to connect between common neural areas from ST1 (ridges) and neural activated regions for behaviors from ST2 (nodes).

The validation of HCP data was verified by previous studies (Smith et al., 2015; Van Essen et al., 2013; Van Essen et al., 2012) and Pilot Study 1 (PS1) in this research. The result of PS1 shows that the dataset provides valid data of fMRI images for each of the behaviors including emotions as well as proxies of cognition such as language, social relationship, working memory, and gambling (problem-solving). However, this ST2 only employed fMRI images used

for making the brain atlas because CCF did not provide a specific fMRI data of consumer decision-making. They do not provide any details about emotions in their fMRI data, thus ST2 attempted to develop a brain map based on what they have provided in their archival fMRI datasets. To investigate the connectivity among neural areas activated for each behavior, ST2 employed an automated anatomical labeling (AAL) atlas to create the region of interest (ROI as a node in the connectivity; Poldrack, 2007; Tzourio-Mazoyer et al., 2002). Then, using HCP data, ST2 attempted to draw a brain map based on neural connectivity between the ROI and the findings (known as a ridge in the connectivity) from the ALE analysis in ST1. ST2 collected 1108 out of 1200 subjects in the HCP datasets after removing missing and invalid data. Analysis and coding processes using MATLAB and R were performed to extract MNI coordinates of each brain activity from the HCP data sets. Using these MNI coordinates and the ALE analysis results, ST2 employed a correlation-based machine learning algorithm in network theory to find neural connectivity among nodes and ridges. The graphical results or connectivity maps are presented in Figures 8 to 11.

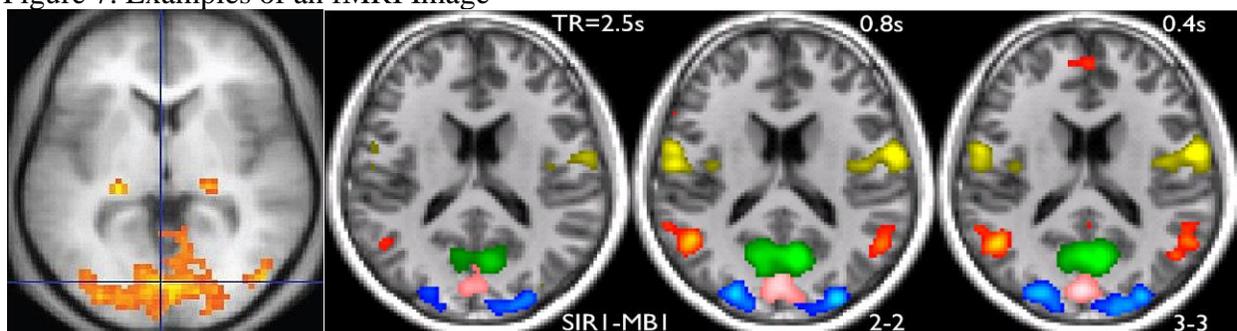
Data

This study used fMRI brain images provided by the Connectome Coordination Facility (CCF) operated by the consortium of Washington University at Saint Louis and University of Minnesota, known as the WU-Minn HCP consortium. The WU-Minn consortium aims to study brain connectivity and function with a genetically-informative design in 1200 individuals using four MR-based modalities plus MEG and EEG (van Essen et al., 2013). Based on researching on brain activity through imaging analysis CCF has provided valuable information that helps to deeper understand what makes human uniquely and what accounts for the great diversity of

behavioral capacities in healthy adults. fMRI fundamentally measures brain activity by detecting changes in blood flow related to energy usages by brain cells, known as blood-oxygen-level dependent (BOLD). This technique is based on the fact that increased blood flow is associated with neural activity (Poldrack, 2011). The image data include meta-data about all participants including demographic information such as age range and sex and behavioral and physiological data such as volume sizes of each brain region for testing behaviors, NEO personality test results, and various types of fMRI datasets including diffusion (dfMRI), resting-state (rfMRI), task-evoked (T-fMRI), T1-T2 MRI, and combined magnetoencephalography and electroencephalography (MEG/EEG) (Van Essen et al., 2013).

For the purpose of using ALE meta-analysis to develop a brain map for consumer decision-making based on the association between cognition and emotions in previous studies, this research used only the t-fMRI data of 1200 subjects who participated in a task-evoked experiment. From the dataset, this research extracted fMRI data of cognitive and emotional behaviors including emotions, working memory, and language. The data of other behaviors in cognition, such as attention and perception, have not yet been released by CCF. Unfortunately, it was also not possible to separate emotions by each affective behavior such as fear, sadness, happiness, disgust, surprise, and anger because CCF has not provided each affective behavior's data yet.

Figure 7. Examples of an fMRI Image



Note: Yellow areas showing increased activity compared with a control condition, modified from Poldrack (2011)

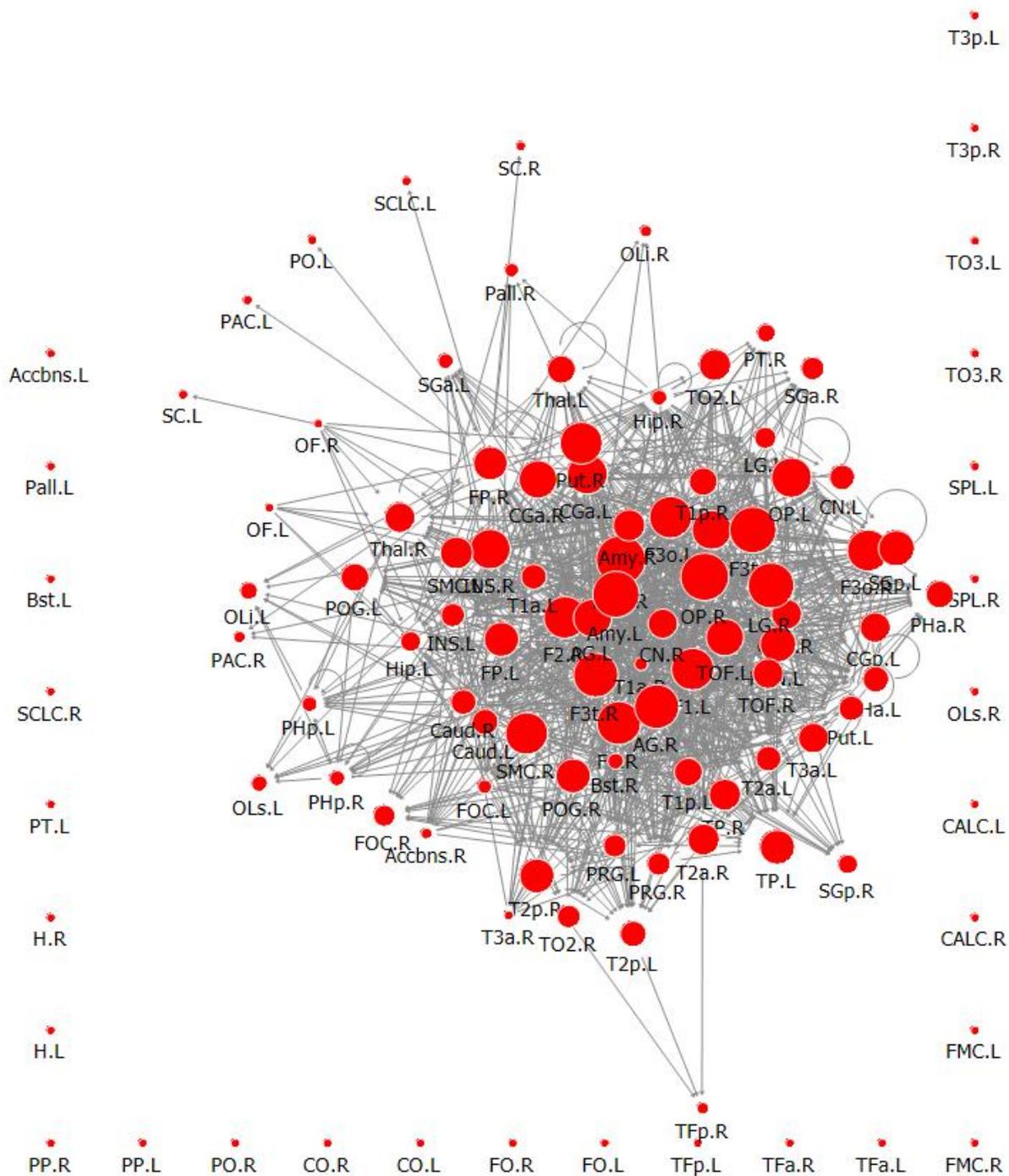
The CCF data sets include a huge amount of information such as brain activity for specific behaviors, demographic information, and metabolic information, about 120 terabytes in total. This study used only about 18 terabytes of specific data of brain activity for both emotional and cognitive behaviors. By analyzing this big data, this study will explore the interaction between brain activity for each behavior in both emotions and cognitions. There were only 1108 participants' brain images used for this study because there were invalid data such as missing information about participants and misreporting images. To safely retain the data, the datasets were stored in secure separate external storages.

Results

ST2 used MNI coordinates to develop a brain map of brain activities for each of emotions and consumer decision-making. For the study, data sets of MNI coordinates from ALE meta-analysis (ST1) and HCP archival image data were employed. Social network analysis was performed to identify neural connectivity for each of the emotions and consumer decision-making. Based on the Harvard-Oxford Atlas (HOA) 112, topological networks created using the Harvard-Oxford Atlas (HOA) 112 are presented in Figures 8 and 9 (emotions), and Figures 10 and 11 (consumer decision-making), respectively. Each graph shows different roles of nodes as levels of in-degree and out-degree. If a node has a higher level of in-degree (large size of red circle), it plays an important role as a receiver which receive incoming data and information from neighbored areas in the link between nodes. If a node has a higher level (large size of red circle) of out-degree, it plays a role as a sender which delivers incoming data and information to neighbored areas in the connection between nodes.

In the connectivity among brain regions for emotions, there are important neural areas that activate for emotions as a receiver, such as the precuneus cortex (PCN, centrality: 0.414), optical pole or visual cortex (OP, centrality: 0.360), inferior frontal cortex (F3t, centrality: 0.351), amygdala (Amy, centrality: 0.351), lingual gyrus (LG, centrality: 0.342), temporal-parietal gyrus (AG, centrality: 0.333), and superior frontal gyrus (F1, centrality: 0.333). The results of receivers' connectivity are presented in Figures 8 and 9.

Figure 8. The Neural Connectivity of Emotions (In-degree)



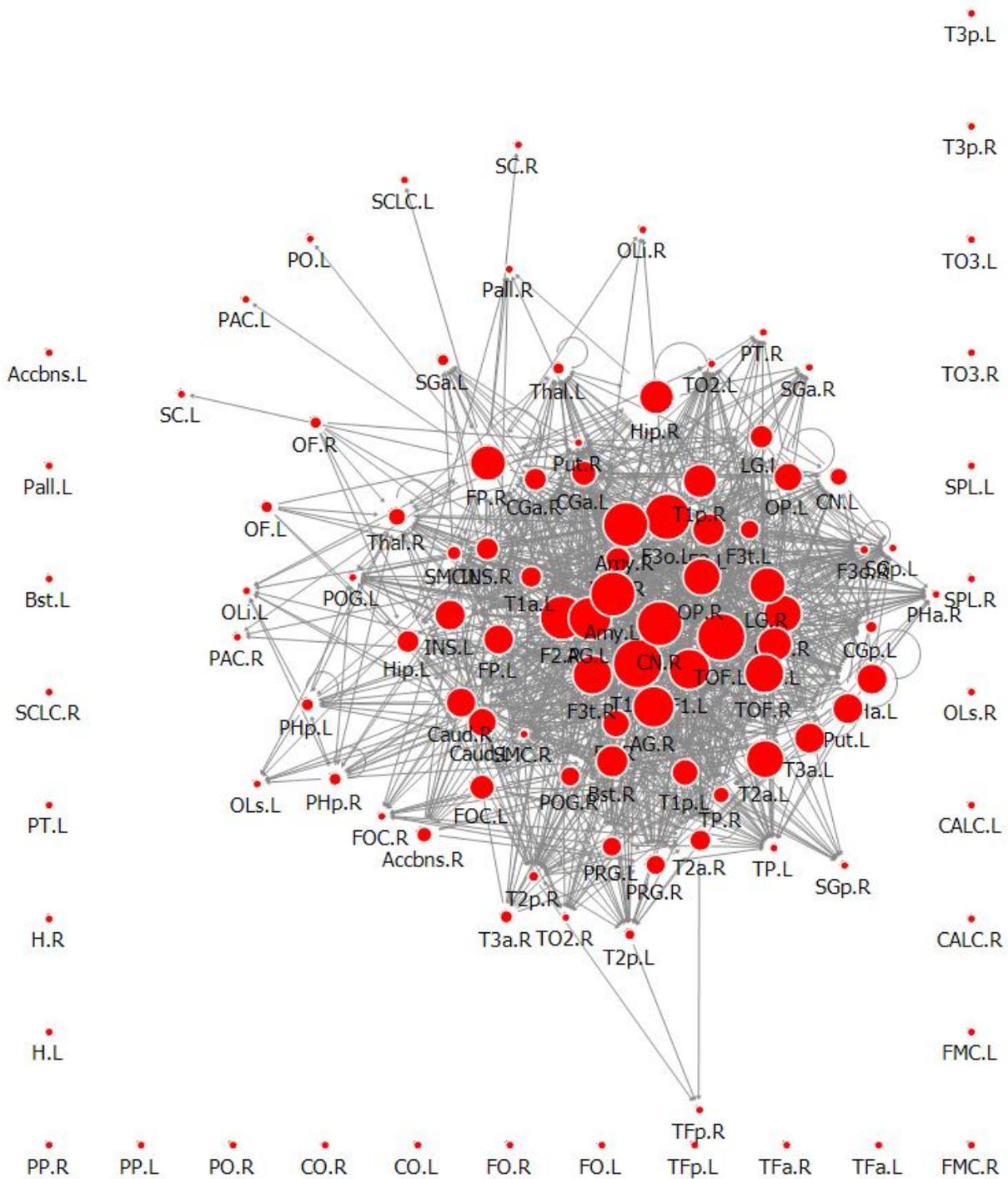
Notes: Larger circle in red means a higher degree of in-degree node. In-degree node is a receiver in the link between nodes.

Other neural areas activate as information senders, including the superior temporal gyrus (T1a, known as Wernicke’s area, Centrality: 0.549), temporal optical fusiform cortex (TOF,

Centrality: 0.477), inferior frontal gyrus/orbitofrontal gyrus (F3o, known as Broca's area, Centrality: 0.450), cuneal cortex (CN, Centrality: 0.441), amygdala (Amy, Centrality: 0.441), middle frontal gyrus (F2, Centrality: 0.432), temporal-parietal gyrus (AG, Centrality: 0.423), superior frontal gyrus (F1, Centrality: 0.387), and inferior frontal gyrus (F3t, Centrality: 0.360).

The results of senders' connectivity are presented in Figure 9.

Figure 9. The Neural Connectivity of Emotions (Out-degree)



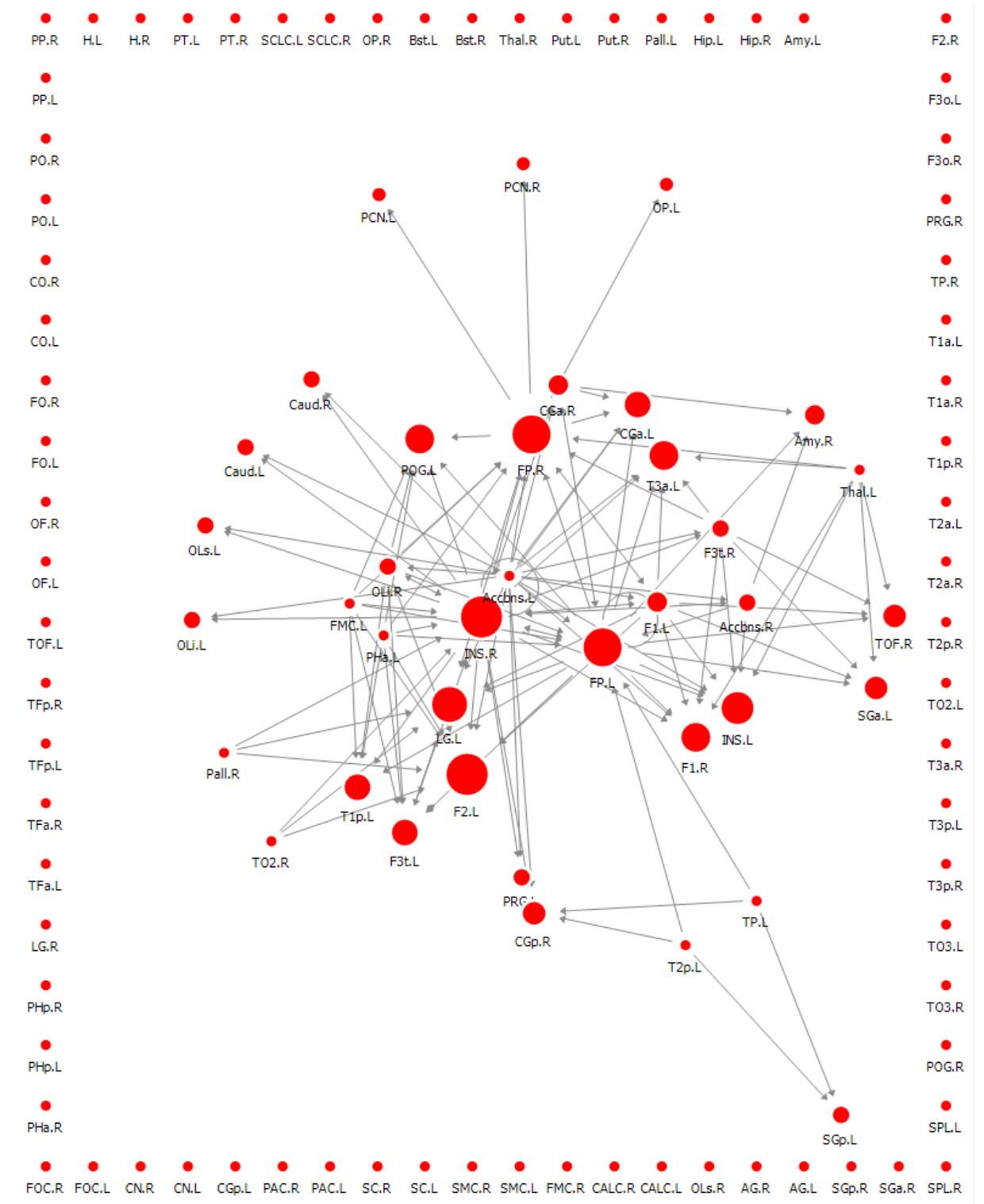
Notes: Larger circle in red means a higher degree of out-degree node. Out-degree node is a sender in the link between nodes.

The results in Figures 8 and 9 show that the superior frontal gyrus (SFG), inferior frontal gyrus (IFG), and amygdala play both roles of receiver and deliverer as a hub of brain activity for

emotions: SFG is located in the frontal lobe which brain is involved in cognitive behaviors such as awareness and coordinating sensory system (Goldberg, Harel, and Malach, 2006). IFG is located in the lowest position of the frontal lobe. It is involved in cognitive behaviors such as language processing and speech production, known as Broca's area (Brodmann area 44, 45, and 47) (Greenlee et al., 2007). The amygdala is located deep inside the temporal lobe which brain is involved in emotional learning, reward, and memory modulation (Maren, 1999).

Neural network analysis for consumer decision-making as a cognitive behavior shows a connectivity pattern seen in Figure 10 and 11. Figure 10 shows that certain brain regions, including the insular cortex (INS, .090), middle frontal gyrus (F2, .090), frontal lobe (FP, .081), lingual gyrus (LG, 0.072), and insular cortex (INS, .063), and amygdala (Amy, 0.027) are in-degree nodes that act as a receiver in the neural connectivity among neural regions for consumer decision-making. Figure 11 shows the neural connectivity and patterns of brain activity and regions (out-degree as a sender) for cognitive behaviors.

Figure 10. The Neural Connectivity of Consumer Decision-making (in-degree)



Notes: Larger circle in red means a higher degree of in-degree node. In-degree node is a receiver in the link between nodes.

Figure 11 includes the neural regions for connectivity of out-degree as a sender, such as insular gyrus (INS, 0.198), accumbens (Accbns, 0.171), frontal lobe (FP, 0.135), superior frontal cortex (F1, 0.081), (lateral) inferior occipital cortex (OLi, 0.128), medial frontal cortex (FMC, 0.063), parahippocampal gyrus (PHa, 0.063), middle temporal gyrus (TO2, 0.027), and pallidum (Pall, 0.027).

The results in Figure 10 and Figure 11 show there are common activated neural areas (hub) for consumer decision-making: insular cortex (BA16), superior frontal gyrus (BA 10, 11 , and 12), middle frontal gyrus (BA 10), and accumbens. Insular cortex has diverse functions including sensory information processing, awareness, and emotions. Especially, insular cortex is activated for emotions with amygdala (Craig & Craig, 2009). Superior frontal cortex activates for awareness and information process to help to make a decision (Goldberg et al., 2006). Accumbens responds to diverse cognitive functions such as sensory information processing and reward. In particular, accumbens is centrally involved in negative emotions such as fear (Schwienbacher et al., 2004).

To verify the degree of each component or node in the networks for emotions and cognition, this study tested the degree of centrality in networks. The concept of centrality refers to how important a node is in the network. This study tested three different types of centrality: degree centrality, closeness centrality, and betweenness centrality (Luke, 2015; Scott, 2000). Degree centrality shows the direct power of a node in a network by calculating the number of connections of the node with others in the network (Scott, 2000). Closeness refers to the time needed to transfer information among nodes and is calculated by the distance between nodes, $C_C(v) = \frac{1}{\sum_{i \neq v} d(v,i)}$, where v is a node, i is the last node, and d is the distance between a node (v) and another node (i) (Scott, 2000). Betweenness means that a node is able to connect between other nodes as a mediator and is calculated by $C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$, where v is a node and $\sigma_{st}(v)$ is the shortest path between nodes (s) and (t) passing through node v . Testing this concept is meaningful to understand the degree of the robustness of network. The results of testing the different types of centrality are presented in Table 14.

Table 14. The Results of Testing Overall Centrality of Networks

	Mean		SD		Min.		Max.		Centralization Index (%)	
	I-D	O-D	I-D	O-D	I-D	O-D	I-D	O-D	I-D	O-D
Emotions										
Degree	.131	.131	.121	.152	.000	.000	.414	.55	28.593	42.229
Closeness	.232	.229	.148	.214	.000	.000	.438	.585	17.950	18.262
Betweenness	.003		.005		.000		.035		3.255	
Cognition										
Degree	.010	.001	.021	.031	.000	.000	.009	.198	8.051	18.96
Closeness	.020	.021	.035	.050	.000	.000	.100	.208	1.344	2.204
Betweenness	.000		.002		.000		.019		1.834	

Notes: SD = standard deviation, Min. = minimum, Max. = maximum, I-D = in-degree, O-D = out-degree

Based on the results of testing centrality, this study found relevant neural nodes for emotions and cognition. For the network of emotions, in-degree nodes including the precuneus cortex, optical pole, inferior frontal gyrus, amygdala, and lingual cortex have higher levels of centrality, while there are out-degree nodes including superior temporal gyrus, inferior frontal gyrus, temporal occipital fusiform gyrus, amygdala, cuneal cortex, and angular gyrus. For the network of cognition, there are in-degree nodes including the supplementary motor cortex, angular gyrus, precuneus cortex, superior frontal cortex, and insula, while there are neural nodes for out-degree such as the frontal lobe, inferior frontal gyrus, middle frontal gyrus, accumbens, and precuneus cortex.

The results of the network analysis are presented in Table 15. It provides scientific evidence that the cognitive and emotional neural regions work together to make a decision or engage in a behavior. This is because the network of emotions regarding betweenness has brain regions for emotions including the frontal lobe, inferior frontal gyrus, inferior frontal gyrus, and middle frontal gyrus as mediating nodes, while the network of decision-making has brain regions

for decision-making including the insular cortex and anterior cingulate cortex as mediating nodes.

Table 15. Central Nodes of Each Behavior

Behavior	Centrality									
	Degree				Closeness				Betweenness	
	In-degree		Out-degree		In-degree		Out-degree			
Emotions	PCN	.414	T1a	.549	PCN	.438	T1a	.585	FP	.035
	OP	.360	F3o	.477	OP	.405	TOF	.537	F3t	.022
	F3t	.351	TOF	.450	F3t	.400	F3o	.527	Amy	.019
	Amy	.351	Amy	.441	Amy	.400	Amy	.514	F3o	.017
	LG	.342	CN	.441	LG	.395	AG	.510	F2	.016
CDM	INS	.090	INS	.198	FP	.100	INS	.207	INS	.018
	F2	.090	Accbn	.171	F2	.100	Accbn	.194	FP	.008
	FP	.081	FP	.135	LG	.100	FP	.172	F1	.004
	LG	.072	F1	.081	INS	.096	FMC	.148	F3t	.001
	F1	.063	OLi	.063	F1	.092	PHa	.147	CGa	.001

Notes: PCN = precuneus cortex, OP = optical pole, F3t = inferior frontal gyrus, Amy = amygdala, LG = lingual gyrus, T1a = superior temporal gyrus, F3o = inferior frontal gyrus, TOF = temporal occipital fusiform cortex (fusiform), CN = cuneal cortex, FP = frontal lobe, F2 = middle frontal gyrus, SMC = supplementary motor cortex, F1 = superior frontal cortex, INS = insula, Accbn = accumbens, CGp = posterior cingulate gyrus, AG = angular gyrus (inferior parietal lobe/temporal parietal gyrus), T1p = posterior superior temporal gyrus, LG = lingual gyrus, PHa = parahippocampal gyrus, CGa = anterior cingulate cortex, CDM = consumer decision-making

CHAPTER V

CONCLUSIONS AND DISCUSSION

Two rival theories have contributed to helping better understand the consumer decision-making process in the marketing discipline: the cognitive perspective (Bettman et al., 1998) and the experiential perspective (Holbrook & Hirschman, 1982). However, the literature has been silent on the alternative perspective that cognitions and emotions work coincidentally and affect each other since there has been no methodological advance in the discipline allowing for this alternative perspective (Shaw & Bagozzi, 2018). With the advent of neuroscientific methods such as fMRI, this gap can be filled. This research attempted to provide empirical evidence that supports the alternative perspective. Although marketing researchers have hypothesized or assumed that cognitions and emotions are associated when an individual engages in a behavior, there has not been scientific evidence to support these theoretical arguments because of the limitations of research methods.

Using neuroscientific and analytical methods, this research was designed to reach two important aims: (a) investigating the association between brain activity for emotional and cognitive behaviors to challenge existing theories (cognitive perspective and experiential perspective) of consumer decision-making in the marketing discipline, and (b) discovering brain connectivity among brain regions for emotions and consumer decision-making to develop neural connectivity which can be illustrated as a map.

ST1 used ALE meta-analysis to find scientific evidence supporting the idea that cognitions and emotions work together even if consumers are in situation in which they only perform either cognitive perspective or emotional perspective. The ALE meta-analysis showed the neural areas activated for the emotional and cognitive behaviors and the common neural areas activated for both behaviors. These findings are physiologically and behaviorally important for marketing research, especially for consumer research, because most existing studies are in neuroscience and there are very few publications in consumer research using neuroscientific methods. Thus, the study contributes to consumer research, especially research on the process of engaging in a behavior, by providing neurological and physiological knowledge about consumer behavior including emotions and decision-making through an analysis of neural data. Existing studies have focused on a limited region of the brain because of the limitations of using neuroscientific methods and difficulties in sampling. ST1 is novel in that it employed a meta-analysis to overcome these limitations and found neural areas associated with a large number of behaviors in cognitions and emotions because ALE analysis of consumer decision-making provided evidence that shows neural activated regions for emotional behaviors control the cognitive behavior, and another ALE analysis of emotions also provided empirical supports by showing brain regions for consumer decision-making also activate for emotions.

ST2 took a neuroscientific approach and used advanced mathematical programs to analyze neuroimages in order to explore the neural connectivity between brain activity for all emotional and cognitive behaviors. The findings in ST2 also support the alternative perspective by showing the functional connectivity among brain regions for diverse behaviors. Unlike previous studies which used a small sample to visualize functional neural connectivity, ST2 employed a large dataset (18 terabytes of fMRI data from 1108 subjects) to analyze the

behavioral and neurological information of neuroimages and visualize a brain connectivity map. Thus, this study was able to show a pattern of neural connectivity among brain activity on different behaviors and to generalize the theoretical assumption that brain regions for both cognitive and emotional behaviors are associated or correlated.

Managerial Implications

The results of this research provide scientific evidence that there are neural co-activations for emotions and cognition in the brain when making a decision. This evidence can be helpful for marketing practitioners when they attempt to communicate with customers. There are various marketing actions and programs that help companies establish better customer relationships through effective and efficient communication such as advertising, mobile applications, social media networks, direct mailing, corporate social responsibility activities, sponsorship, and customized relationship marketing (Keller, 2013). As the results showed in ST1 and ST2, consumers make a decision based on co-activations of different neural areas. This research collected studies that used written messages and videos or pictures as stimuli that cause brain activity. Even though there are numerous types of brain activity patterns, there is a co-activation pattern in the neural areas for cognitive and emotional behaviors. Based on the results, we can logically assume that regardless of the types of stimuli, consumers use both neural regions for emotional and cognitive behaviors. Thus, companies should learn about how to develop effective and efficient ways of delivering a message about products/services/brands by appealing to both cognitive and emotional aspects.

Even though this research shows the co-activation of neural areas for both emotions and consumer decision-making, each consumer has his or her own personality type. Therefore, it is

important to understand consumer behaviors based on each personality type and develop customized marketing programs for different personality types and patterns of behaviors related to personality. This practical suggestion is supported by previous findings that various brain areas are activated for each personality type including neuroticism, extraversion, openness, agreeableness, and conscientiousness (Aaker, 1997; Costa & McCrae, 1992; Chang et al., 2019; Chen, 2007). It does not mean all consumers are in each of the categories of the personality. However, the physiological categories would help marketers who do market research to learn more about customers' needs and wants by showing scientific patterns of consumer behaviors. Thus, it is important for companies to be able to pay attention to learn more deeply about consumer behaviors, such as satisfaction, re/purchase intention, and attitudes toward products, services, and brands, by using accurate research methods on customers.

Limitations and Future Research Agendas

This is a data-driven study, which means the results come from data without theoretical assumption or fundamental theories. The purpose of this study was to investigate the interaction between cognitive and emotional behaviors to support the alternative perspective that when consumers engage in a behavior such as decision-making, problem-solving, or brand judgement or preference, they are not only using cognitive abilities but also emotional understandings. Future researchers should utilize experimental research designs using an fMRI machine to make more theoretical and contributions to consumer behavior and consumer neuroscience.

This research only collected data from healthy young adults (age 21 to 40) who participated in fMRI studies. A reason of the collection was to see more healthy and concrete brain activities among emotions and cognition of healthy and young adults than other

populations such as children and old generation groups. Furthermore, the HCP data came only from healthy young adults. Studying brain activity among emotions and decision-making in other groups such as children and older people would provide meaningful insights about group difference in brain activity for emotions and decision-making and neural activity in mapping consumer decision-making and emotions.

Another limitation is the inability to analyze different factors such as demographic and biophysical data (sex, personality, age, etc.) that affect changes in brain activity for specific behaviors. For instance, this research confirmed that there are different brain regions activated for each personality type. Future researchers should examine the differences in activated brain regions in different groups such as male/female, healthy/unhealthy, and old/young.

Lastly, this research was a coordinate-based meta-analysis. As discussed earlier, there are two different types of meta-analysis: coordinate-based meta-analysis (CBMA) and image-based meta-analysis (IBMA). A way to analyze image data without transforming image information into numerical information would be to compare areas or surfaces of target or activated brain regions by analyzing multi-voxel patterns (Oosterhof, Wiestler, Downing, & Diedrichsen, 2011). It would be shapelier in visualizing brain areas or regions with considering neighbored brain regions than CBMA has a limitation in considering overlapped or neighbors of target brain region.

REFERENCES

- Aaker, J. L. (1997). Dimensions of brand personality. *Journal of Marketing Research*, 34(3), 347-356.
- Abi-Jaoude, E., Segura, B., Cho, S. S., Crawley, A., & Sandor, P. (2018). The neural correlates of self-regulatory fatigability during inhibitory control of eye blinking. *Journal of Neuropsychiatry and Clinical Neurosciences*, 30(4), 325-333.
- Acevedo, B. P., Aron, E. N., Aron, A., Sangster, M. D., Collins, N., & Brown, L. L. (2014). The highly sensitive brain: an fMRI study of sensory processing sensitivity and response to others' emotions. *Brain and behavior*, 4(4), 580-594.
- Acikalin, M. Y., Gorgolewski, K. J., & Poldrack, R. A. (2017). A coordinate-based meta-analysis of overlaps in regional specialization and functional connectivity across subjective value and default mode networks. *Frontiers in Neuroscience*, 11(1), 1-11.
- Adolphs, R., Tranel, D., & Damasio, A. R. (2003). Dissociable neural systems for recognizing emotions. *Brain and Cognition*, 52(1), 61-69.
- Alia-Klein, N., Preston-Campbell, R. N., Moeller, S. J., Parvaz, M. A., Bachi, K., Gan, G., ... & Goldstein, R. Z. (2018). Trait anger modulates neural activity in the fronto-parietal attention network. *PloS One*, 13(4), 1-14. doi:doi.org/10.1371/journal.pone.0194444
- Al-Kwafi, S. O. (2016). The role of fMRI in detecting attitude toward brand switching: An exploratory study using high technology products. *Journal of Product & Brand Management*, 25(2), 208-218.
- Alpaydin, E. (2014). *Introduction to machine learning*. Cambridge, MA: MIT Press.
- Andrews-Hanna, J. R., Smallwood, J., & Spreng, R. N. (2014). The default network and self-generated thought: Component processes, dynamic control, and clinical relevance. *Annals of the New York Academy of Sciences*, 1316(1), 29-52.
- Argyle, M. (2002). *The psychology of happiness* (2nd ed.). East Sussex, UK: Routledge.
- Ariely, D., & Berns, G. S. (2010). Neuromarketing: The hope and hype of neuroimaging in business. *Nature Reviews Neuroscience*, 11(4), 284-292.
- Armony, J. L., & Dolan, R. J. (2002). Modulation of spatial attention by fear-conditioned stimuli: an event-related fMRI study. *Neuropsychologia*, 40(7), 817-826.

- Armstrong, K. M., Fitzgerald, J. K., & Moore, T. (2006). Changes in visual receptive fields with microstimulation of frontal cortex. *Neuron*, 50(5), 791–798.
- Arslan, S., Ktena, S. I., Makropoulos, A., Robinson, E. C., Rueckert, D., & Parisot, S. (2018). Human brain mapping: A systematic comparison of parcellation methods for the human cerebral cortex. *NeuroImage*, 170(4), 5-30.
- Atkinson, R. C., & Shiffrin, R. M. (1971). The control of short-term memory. *Scientific American*, 225(2), 82-91.
- Baddeley, A. (2007). *Working memory, thought, and action* (Vol. 45). New York, NY: Oxford University Press.
- Baddeley, A. (2017). *Exploring working memory*. London, UK: Taylor & Francis Group.
- Bakker, A., Albert, M. S., Krauss, G., Speck, C. L., & Gallagher, M. (2015). Response of the medial temporal lobe network in amnesic mild cognitive impairment to therapeutic intervention assessed by fMRI and memory task performance. *NeuroImage: Clinical*, 7, 688-699.
- Baldour, C. L., & Feldner, M. T. (2018). The role of disgust in posttraumatic stress: A critical review of the empirical literature. *Journal of Experimental Psychology*, 9(3), 1-26.
- Banks, S. J., Eddy, K. T., Angstadt, M., Nathan, P. J., & Phan, K. L. (2007). Amygdala–frontal connectivity during emotion regulation. *Social cognitive and affective neuroscience*, 2(4), 303-312.
- Barrett, J., Pike, B., & Paus, T. (2004). The role of the anterior cingulate cortex in pitch variation during sad affect. *European Journal of Neuroscience*, 19(2), 458-464.
- Barrett, L. (2017). *How emotions are made*. New York, NY: Houghton Mifflin Harcourt.
- Barrett, L. F. (2017). The theory of constructed emotion: An active inference account of interoception and categorization. *Social Cognitive and Affective Neuroscience*, 1, 1-23.
- Bartolo, A., Benuzzi, F., Nocetti, L., Varaldi, P., & Nichello, P. (2006). Humor comprehension and appreciation: An fMRI study. *Journal of Cognitive Neuroscience*, 18(11), 1789-1798.
- Beaty, R. E., Benedek, M., Silvia, P. J., & Schacter, D. L. (2016). Creative cognition and brain network dynamics. *Trends in Cognitive Sciences*, 20(2), 87-95.
- Belin, P., Zatorre, R. J., Lafaille, P., Ahad, P., & Pike, B. (2000). Voice-selective areas in human auditory cortex. *Nature*, 403(6767), 303-312.
- Benuzzi, F., Meletti, S., Zamboni, G., Calandra-Buonaura, G., Serafini, M., Lui, F., ... & Nichelli, P. (2004). Impaired fear processing in right mesial temporal sclerosis: a fMRI study. *Brain research bulletin*, 63(4), 269-281.

- Berger, P., Bitsch, F., Nagels, A., Straube, B., & Faleknberg, I. (2018). Personality modulates amygdala and insula connectivity during humor appreciation: An event-related fMRI study. *Social Neuroscience, 13*(6), 756-768.
- Berl, M. M., Mayo, J., Parks, E. N., Rosenberger, L. R., VanMeter, J., Ratner, N. B., ... & Gaillard, W. D. (2014). Regional differences in the developmental trajectory of lateralization of the language network. *Human Brain Mapping, 35*(1), 270-284.
- Berns, G. S., & Moore, S. E. (2012). A neural predictor of cultural popularity. *Journal of Consumer Psychology, 22*(1), 154-160.
- Berridge, K. C., & Kringelbach, M. L. (2015). Pleasure systems in the brain. *Neuron, 86*(3), 646-664.
- Berridge, K. C., Robinson, T. E., & Aldridge, J. W. (2009). Dissecting components of reward: 'liking', 'wanting', and learning. *Current Opinion of Pharmacology, 9*(1), 65-73.
- Bettman, J. R. (1979). Memory factors in consumer choice: A review. *Journal of Marketing, 43*(2), 37-53.
- Bettman, J. R., Luce, M. F., & Payne, J. W. (1998). Constructive consumer choice processes. *Journal of Consumer Research, 25*(3), 187-217.
- Bettman, J. R., & Zins, M.A. (1979). Information format and choice task effects in decision-making. *Journal of Consumer Research, 6*(2), 141-153.
- Blair, K. S., Smith, B. W., Mitchell, D. G., Morton, J., Vythilingam, M., Pessoa, L., ... & Pine, D. S. (2007). Modulation of emotion by cognition and cognition by emotion. *Neuroimage, 35*(1), 430-440.
- Bogert, B., Numminen-Kontti, T., Gold, B., Sams, M., Numminen, J., Burunat, I., ... & Brattico, E. (2016). Hidden sources of joy, fear, and sadness: explicit versus implicit neural processing of musical emotions. *Neuropsychologia, 89*, 393-402.
- Brattico, E., Alluri, V., Bogert, B., Jacobsen, T., Vartiainen, N., Nieminen, S., & Tervaniemi, M. (2011). A functional MRI study of happy and sad emotions in music with and without lyrics. *Frontier in Psychology, 2*, 1-16.
- Bray, S., Rangel, A., Shimojo, S., Balleine, B., & O'Doherty, J. P. (2008). The neural mechanisms underlying the influence of Pavlovian cues on human decision-making. *Journal of Neuroscience, 28*(22), 5861-5866.
- Brooks, J. O., Vizueta, N., Penfold, C., Townsend, J. D., Bookheimer, S. Y., & Altshuler, L. L. (2015). Prefrontal hypoactivation during working memory in bipolar II depression. *Psychological Medicine, 45*(8), 1731-1740.
- Brugger, M., Ettl, D. A. Meier, M., Keller, T., Luechinger, R., Barlow, A., Palla, S., Jancke, L., & Lutz, K. (2011). Taking sides with pain - Lateralization aspects related to cerebral processing of dental pain. *Frontiers in Human Neuroscience, 5*(12), 1-13.

- Buades-Rotger, M., Beyer, F., & Krämer, U. M. (2017). Avoidant responses to interpersonal provocation are associated with increased amygdala and decreased mentalizing network activity. *eNeuro*, 4(3), 1-16.
- Burgdorf, J., & Panksepp, J. (2006). The neurobiology of positive emotions. *Neuroscience and Biobehavioral Reviews*, 30(2), 173-187.
- Cacioppo, J. T., Petty, R., Kao, C. F., & Rodriguez, R. (1986). Central and peripheral routes to persuasion: An individual difference perspective. *Journal of Personality and Social Psychology*, 51(5), 1032-1043.
- Cao, M., Shu, N., Cao, Q., Wang, Y., & He, Y. (2014). Imaging functional and structural brain connectomics in attention-deficit/hyperactivity disorder. *Molecular Neurobiology*, 50(3), 1111-1123.
- Capitão, L. P., Chapman, R., Murphy, S. E., Harvey, C. J., James, A., Cowen, P. J., & Harmer, C. J. (2019). A single dose of fluoxetine reduces neural limbic responses to anger in depressed adolescents. *Translational psychiatry*, 9(1), 30.
- Carmichael, S. T., Clugnet, M. C., & Price, J. L. (1994). Central olfactory connections in the macaque monkey. *Journal of Comparative Neurology*, 346(3), 403-434.
- Cartmell, S. C., Chun, M. M., & Vickery, T. J. (2013). Neural antecedents of social decision-making in a partner choice task. *Social Cognitive and Affective Neuroscience*, 9(11), 1722-1729.
- Casarotto, S., Ricciardi, E., Romani, S., Dalli, D., & Pietrini, P. (2013). Covert brand recognition engages emotion-specific brain networks. *Archives Italiennes de Biologie*, 150(4), 259-273.
- Caspers, S., Ziles, K., Laird, A.R., & Eickhoff, S.B. (2010). ALE meta-analysis of action observation and imitation in the human brain. *NeuroImage*, 50(3), 1148-1167.
- Kastner, S., & Ungerleider, S. (2000). Mechanisms of visual attention in the human cortex. *Annual Review of Neuroscience*, 23, 315-341
- Chang, H. H., Vitell, S. J., & Lu, L. C. (2019). Consumers' perceptions regarding questionable consumption practices in China: The impacts of personality. *Asia Pacific Journal of Marketing and Logistics*, 31(3), 592-608.
- Chen, M. F. (2007). Consumer attitudes and purchase intentions in relation to organic foods in Taiwan: Moderating effects of food-related personality traits. *Food Quality and Preference*, 18(7), 1008-1021.
- Cherry, J. B. C., Bruce, J. M., Lusk, J. L., Crespi, J. M., Lim, S. L., & Bruce, A. S. (2015). Neurofunctional correlates of ethical, food-related decision-making. *PloS One*, 10(4), 1-16.

- Chi, T., Ru, P., & Shamma, S. A. (2005). Multiresolution spectrotemporal analysis of complex sounds. *Journal of the Acoustical Society of America*, *118*(2), 887-906.
- Choi, S., Liu, S. Q., & Mattila, A. S. (2018). Consumer response to authentic-language versus English-language menu labeling in ethnic dining. *Cornell Hospitality Quarterly*, *59*(2), 125-134.
- Cieslik, E. C., Zilles, K., Caspers, S., Rosli, C., Kellermann, T. S., Jakobs, O., ... & Eickhoff, S. B. (2013). Is there “one” DLPFC in cognitive action control? Evidence for heterogeneity from co-activation based parcellation. *Cerebral Cortex*, *23*(11), 2677-2689.
- Connor, C. E., Egeth, H. E., & Yantis, S. (2004). Visual attention: Bottom-up versus top-down. *Current Biology*, *14*, R850–R852
- Corradi-Dell’Acqua, C., Tusche, A., Vuilleumier, P., & Singer, T. (2016). Cross-modal representations of first-hand and vicarious pain, disgust and fairness in insular and cingulate cortex. *Nature Communications*, *7*(March), 1-12.
- Costa, P. T., & McCrae, R. R. (1985). *The NEO Personality Inventory manual*. Odessa, FL: Psychological Assessment Resources.
- Costa, P. T., & McCrae, R. R. (1992). Normal personality assessment in clinical practice: The NEO Personality Inventory. *Psychological Assessment*, *4*(1), 5-13.
- Costafreda, S. G., David, A. S., & Brammer, M. J. (2009). A parametric approach to voxel-based meta-analysis. *NeuroImage*, *46*(1), 115-122.
- Craig, A. D., & Craig, A. D. (2009). How do you feel--now? The anterior insula and human awareness. *Nature Reviews Neuroscience*, *10*(1), 59-70.
- Creswell, J. D., Bursley, J. K., & Satpute, A. B. (2013). Neural reactivation links unconscious thought to decision-making performance. *Social Cognitive and Affective Neuroscience*, *8*(8), 863-869.
- Crotts, J. C., & Magnini, V. P. (2011). The customer delight construct: Is surprise essential? *Annals of Tourism Research*, *38*(2), 719-722.
- Cui, J., Xu, L., Bressler, S. L., Ding, M., & Liang, H. (2008). BSMART: A Matlab/C toolbox for analysis of multichannel neural time series. *Neural Networks*, *21*(8), 1094-1104.
- Dalenberg, J. R., Weitkamp, L., Renken, R. J., Nanetti, L., & ter Horst, G. J. (2017). Flavor pleasantness processing in the ventral emotion network. *PloS one*, *12*(2), e0170310.
- Damasio, A. R. (1994). *Descartes’ error: emotions, reason, and the human brain*. New York, NY: Avon Books.
- Damasio, A. R. (2003). *Looking for Spinoza: Joy, sorrow, and the feeling brain*. Orlando, FL: Houghton Mifflin Harcourt.

- Decety, J., & Jackson, P. L. (2004). The functional architecture of human empathy. *Behavioral and Cognitive Neuroscience Reviews*, 3(2), 71-100.
- De Martino, B., Bobadilla-Suarez, S., Nouguchi, T., Sharot, T., & Love, B. C. (2017). Social information is integrated into value and confidence judgments according to its reliability. *Journal of Neuroscience*, 37(25), 6066-6074.
- Deppe, M., Schwindt, W., Kugel, H., Plassmann, H., & Kenning, P. (2005). Nonlinear response within the medial prefrontal cortex reveal when specific implicit information influences economic decision-making. *Journal of Neuroimaging*, 15(2), 171-182.
- Deppe, M., Schwindt, W., Pieper, A., Kugel, H., Plassmann, H., Kenning, P., ... & Ringelstein, E. B. (2007). anterior cingulate reflects susceptibility to framing during attractiveness evaluation. *Neuroreport*, 18(11), 1119-1123.
- Diano, M., Celeghin, A., Bagnis, A., & Tamietto, M. (2017). Amygdala response to emotional stimuli without awareness: facts and interpretations. *Frontiers in psychology*, 7, 2029.
- Disgust. (2019, March 5). In *Merriam-Webster.com*. Retrieved from: <https://www.merriam-webster.com/dictionary/disgust>
- Dolan, R. J. (2002). Emotion, cognition, and behavior. *Science*, 298(8), 1191-1194.
- Dolcos, S., Sung, K., Argo., J.J., Flor-Henry, S., & Dolcos, F. (2012). The power of a handshake: Neural correlates of evaluative judgments in observed social interactions. *Journal of Cognitive Neuroscience*, 24(12), 2292-2305.
- Donavan, T., Minor, M. S., & Mowen, J. (2016). *Consumer behavior*. Chicago, IL: Chicago Business Press.
- Doyon, J., Laforce, R., Bouchard, G., Gaudreau, D., Roy, J., Poirier, M., ... & Bouchard, J.P. (1998). Role of the striatum, cerebellum and frontal lobes in the automatization of a repeated visuomotor sequence of movements. *Neuropsychologia*, 36(7), 625-641.
- Duncan, J., & Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological Review*, 96(3), 433-458.
- Durand, F., Issac, C., & Januel, D. (2019). Emotional memory in post traumatic stress disorder: A systematic PRISMA review of controlled studies. *Frontiers in Psychology*, 10(303), 10.303.
- Eichenbaum, H. (2000). A cortical-hippocampal system for declarative memory. *Nature Reviews Neuroscience*, 1, 41-50.
- Egan, V., Deary, I., & Austin, E. (2000). The NEO-PI: Emerging British norms and an item-level analysis suggest N, A, C are more reliable than O and E. *Personality and Individual Differences*, 29(5), 907-920.

- Egner, T., Monti, J. M., & Summerfield, C. (2010). Expectation and surprise determine neural population responses in the ventral visual stream. *Journal of Neuroscience*, *30*(49), 16601-16608.
- Eickhoff, S. B., Bzdok, D., Laird, A. R., Roski, C., Caspers, S., Zilles, K., & Fox P. T. (2011). Co-activation patterns distinguish cortical modules, their connectivity and functional differentiation. *NeuroImage*, *57*, 938-949.
- Eickhoff, S. B., Bzdok, D., Laird, A. R., Kruth, F., & Fox, P. T. (2012). Activation likelihood estimation meta-analysis revisited. *NeuroImage*, *59*(3), 2349-2361.
- Eickhoff, S. B., Laird, A. R., Grefkes, C., Wang, L. E., Ziles, K., & Fox, P. T. (2009). Coordinate-based activation likelihood estimation meta-analysis of neuroimaging data: A random effects approach based on empirical estimates of spatial uncertainty. *Human Brain Mapping*, *30*(9), 2907-2926.
- Ekinici, Y., & Dawes, P. L. (2009). Consumer perceptions of frontline service employee personality traits, interaction quality, and consumer satisfaction. *The Service Industries Journal*, *29*(4), 503-521.
- Ekman, P. (1972). Universals and cultural differences in facial expressions of emotion. In J. Cole, *Nebraska Symposium on Motivation* (pp. 207-283). Lincoln, NE: University of Nebraska Press.
- Ekman, P. (1992). An argument for basic emotions. *Cognition & Emotion*, *6*(3-4), 169-200.
- Ekman, P. (2000). Facial expressions. In T. Dalgleish & M. Power, *Handbook of cognition and emotion* (pp. 301-320). Chichester, UK: John Wiley & Sons.
- Erk, S., Spitzer, M., Wunderlich, A. P., Galley, L., & Walter, H. (2002). Cultural objects modulate reward circuitry. *NeuroReport*, *13*(18), 2499-2503.
- Esch, F. R., Moll, T., Schmitt, B., Elger, C. E., Neuhaus, C., & Weber, B. (2012). Brands on the brain: Do consumers use declarative information or experienced emotions to evaluate brands? *Journal of Consumer Psychology*, *22*(1), 75-85.
- Euler, L. (1953). Leonhard Euler and the Königsberg bridges. *Scientific American*, *189*(1), 66-72.
- Eysenck, M. W. (2012). *Simply psychology*. London, UK: Psychology Press.
- Farrow, T. F., Zheng, Y., Wilkinson, I. D., Spence, S. A., Deakin, J. W., Tarrier, N., ... & Woodruff, P. W. (2001). Investigating the functional anatomy of empathy and forgiveness. *Neuroreport*, *12*(11), 2433-2438.
- Felleman, D. J., & Van Essen, D. C. (1991). Distributed hierarchical processing in the primate cerebral cortex. *Cerebral Cortex*, *1*, 1-47

- Fields, H. L., Hjelmstad, G. O., Margolis, E. B., & Nicola, S. M. (2007). Ventral tegmental area neurons in learned appetitive behavior and positive reinforcement. *Annual Review of Neuroscience*, *30*, 289-316.
- Finn, E.S., Shen, X., Scheinost, D., Rosenberg, M.D., Huang, J., Chun, M.M., Papademetris, X., & Constable, R.T. (2015). Functional connectome fingerprinting: Identifying individuals based on patterns of brain connectivity. *Nature Neuroscience*, *18*(11), 1664-1671.
- Friston, K. J. (2005). Models of brain function in neuroimaging. *Annual Review of Psychology*, *56*, 57-87.
- Frith, U., & Frith, C. (2001). The biological basis of social interaction. *Current Directions in Psychological Science*, *10*(October), 151-155.
- Fujiwara, J., Usui, N., Park, S. Q., Williams, T., Iijima, T., Taira, M., ... & Tobler, P. N. (2013). Value of freedom to choose encoded by the human brain. *Journal of neurophysiology*, *110*(8), 1915-1929.
- Gallagher, H. L., & Frith, C. D. (2003). Functional imaging of “Theory of Mind”. *Trends in Cognitive Sciences*, *7*(February), 77-83.
- Gasquoine, P. G. (2016). *Neuropsychology: Cellular physiology to clinical practice* (2nd ed.). Redding, CA: BVT Publishing.
- Gazzaniga, M. S. (2009). *The cognitive neurosciences* (4th ed.). Cambridge, MA: MIT Press.
- Geissmann, L., Gschwind, L., Schickanz, N., Deuring, G., Rosburg, T., Schweigler, K., ... & Coynel, D. (2018). Resting-state functional connectivity remains unaffected by preceding exposure to aversive visual stimuli. *NeuroImage*, *167*, 354-365.
- Gilam, G., Abend, R., Gurevitch, G., Erdman, A., Baker, H., Ben-Zion, Z., & Hendler, T. (2018). Attenuating anger and aggression with neuromodulation of the vmPFC: A simultaneous tDCS-fMRI study. *Cortex*, *109*, 156-170.
- Glasser, M. F., Smith, S. M., Marcus, D. S., Andersson, J. L., Auerbach, E. J., Behrens, T. E., ... & Robinson, E. C. (2016). The Human Connectome Project’s neuroimaging approach. *Nature Neuroscience*, *19*(9), 1175-1187.
- Goldberg, I., Harel, M., & Malach, R. (2006). When the brain loses its self: Prefrontal inactivation during sensorimotor processing. *Neuron*, *50*(2), 329-339.
- Gottfried, J. A., & Dolan, R. J. (2003). The nose smells what the eye sees: Crossmodal visual facilitation of human olfactory perception. *Neuron*, *39*(2), 375-386.
- Göttlich, M., Beyer, F., & Krämer, U. (2015). BASCO: A toolbox for task-related functional connectivity. *Frontiers in Systems Neuroscience*, *9*, 1-10.
- Grahn, J. A., Parkinson, J. A., & Owen, A. M. (2009). The role of the basal ganglia in learning and memory: neuropsychological studies. *Behavioural Brain Research*, *199*(1), 53-60.

- Greenlee, J. D., Oya, H., Kawasaki, H., Volkov, I. O., Severson, M. A., Hoard, M. A., & Brugge, J. F. (2007). Functional connections within the human inferior frontal gyrus. *Journal of Comparative Neurology*, *503*(4), 550-559.
- Griffiths, T. D., Kumar, S., Von Griegenstein, K., Overath, T., Stephan K. E., & Friston, K. J. (2009). Auditory object analysis. In M. S. Gazzaniga, *The cognitive neurosciences* (4th ed., pp. 367-381). Cambridge, MA: Massachusetts Institute of Technology.
- Grosenick, L., Greer, S., & Knutson, B. (2008). Interpretable classifiers for fMRI improve prediction of purchases. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *16*(6), 539-548.
- Habel, U., Klein, M., Kellermann, T., Shah, N. J., & Schneider, F. (2005). Same or different? Neural correlates of happy and sad mood in healthy males. *NeuroImage*, *26*(1), 206-214.
- Haeger, A., Pouzat, C., Luecken, V., N'Diaye, K., Elger, C. E., Kennerknecht, I., ... & Dinkelacker, V. (2018). P34. Working memory for faces in congenital prosopagnosia: altered neural representations in the fusiform face area. *Clinical Neurophysiology*, *129*(8), e80-e81.
- Hannan KL, Wood SJ, Yung AR, Velakoulis D, Phillips LJ, Soulsby B, Berger G, McGorry PD, Pantelis C (June 2010). "Caudate nucleus volume in individuals at ultra-high risk of psychosis: a cross-sectional magnetic resonance imaging study". *Psychiatry Research*. *182*(3), 223–30.
- Hamerman, E. J., & Schneider, A. B. (2018). The role of disgust sensitivity in volunteer recruitment and retention. *International Journal of Nonprofit and Voluntary Sector Marketing*, *23*(2), 1-10.
- Hampshire, A., Chamberlain, S. R., Monti, M. M., Duncan, J., & Owen, A. M. (2010). The role of the right inferior frontal gyrus: inhibition and attentional control. *NeuroImage*, *50*(3), 1313-1319.
- Harris, J. M., Ciorciraci, J., & Gountas, J. (2018). Consumer neuroscience for consumer research. *Journal of Consumer Behavior*, *17*(3), 239-252. doi:doi.org/10.1002/cb.1710
- Havlena, W. J., & Holbrook, M. B. (1986). The varieties of consumption experience: Comparing two typologies of emotion in consumer behavior. *Journal of Consumer Research*, *13*(3), 394-404.
- He, B., Dai, Y., Astolfi, L., Babiloni, F., Yuan, H., & Yang, L. (2011). eConnectome: a MATLAB toolbox for mapping and imaging of brain functional connectivity. *NeuroImage*, *195*(2), 261-269.
- Heesink, L., Gladwin, T. E., Vink, M., van Honk, J., Kleber, R., & Geuze, E. (2018). Neural activity during the viewing of emotional pictures in veterans with pathological anger and aggression. *European Psychiatry*, *47*(January), 1-8.

- Hickok, G. (2009). The cortical organization of phonological processing. In M. S. Gazzaniga, *The Cognitive Sciences* (pp. 767-776). Cambridge, MA: MIT Press.
- Hickok, G., Buchsbaum, B., Humphries, C., & Muftuler, T. (2003). Auditory-motor interaction revealed by fMRI: Speech, music, and working memory in area SPT. *Journal of Cognitive Neuroscience*, *15*(5), 673-682.
- Hickok, G., & Poeppel, D. (2007). The cortical organization of speech processing. *Nature Reviews Neuroscience*, *8*(5), 393-402.
- Holbrook, Morris B. and Elizabeth C. Hirschman. (1982). The experiential aspects of consumption: Consumer fantasies, feeling, and fun. *Journal of Consumer Research*, *9*(2), 132-140.
- Holmes, C. J., Hoge, R., Collins, L., Woods, R., Toga, A. W., & Evans, A. C. (1998). Enhancement of MR images using registration for signal averaging. *Journal of Computer Assisted Tomography*, *22*(2), 324-333.
- Holstege, G., Georgiadis, J. R., Paans, A. M., Meiners, L. C., van der Graaf, F. H., & Reinders, A. S. (2003). Brain activation during human male ejaculation. *Journal of Neuroscience*, *23*(27), 9185-9193.
- Homae, F., Hashimoto, R., Nakajima, K., Miyashita, Y., & Sakai, K. L. (2002). From perception to sentence comprehension: the convergence of auditory and visual information of language in the left inferior frontal cortex. *Neuroimage*, *16*(4), 883-900.
- Hornung, J., Noack, H., Kogler, L., & Derntl, B. (2019). Exploring the fMRI based neural correlates of the dot probe task and its modulation by sex and body odor. *Psychoneuroendocrinology*, *99*, 87-96.
- Hosseini, S. H., Hoefft, F., & Kesler, S. R. (2012). GAT: A graph-theoretical analysis toolbox for analyzing between group differences in large scale structural and functional brain networks. *PLoS One*, *7*(7), e40709.
- Hsu, Y., Fang, W., & Tseng, W. (2016). The effect of surprise on customer satisfaction: The moderating role of status consumption. *International Journal of Business and Information*, *11*(2), 199-232.
- Hubbard, E. M., & Ramachandran, V. S. (2005). Neurocognitive mechanisms of synesthesia. *Neuron*, *48*(3), 509-520.
- Hubert, M., & Kenning, P. (2008). A current overview of consumer neuroscience. *Journal of Consumer Behaviour*, *7*(4-5), 272-292.
- Huddleston, P., Behe, B. K., Minahan, S., & Fernandez, R. T. (2015). Seeking attention: An eye tracking study of in-store merchandise displays. *International Journal of Retail & Distribution Management*, *43*(6), 561-574

- Huijsmans, I., Ma, I., Micheli, L., Civai, C., Stallen, M., & Sanfey, A. G. (2019). A scarcity mindset alters neural processing underlying consumer decision-making. *Proceedings of the National Academy of Sciences*, *116*(24), 11699-11704.
- James, W. (1890). *The principles of psychology*. New York, NY: Henry Holt.
- Jiang, Q., Hou, L., Wang, H., & Li, C. (2018). The Effect of Cognitive Reappraisal on Reactive Aggression: An fMRI Study. *Frontiers in psychology*, *9*, 1903.
- Johnstone, T., Van Reekum, C. M., Oakes, T. R., & Davidson, R. J. (2006). The voice of emotion: an FMRI study of neural responses to angry and happy vocal expressions. *Social Cognitive and Affective Neuroscience*, *1*(3), 242-249.
- Jung, D., Sul, S., Lee, M., & Kim, H. (2018). Social observation increases functional segregation between MPFC subregions predicting prosocial consumer decisions. *Scientific Reports*, *8*(1), 1-13.
- Kang, M. J., & Camerer, C. F. (2013). fMRI evidence of a hot-cold empathy gap in hypothetical and real aversive choices. *Frontiers in Neuroscience*, *7*(104), 1-16.
- Kang, M. J., Rangel, A., Camus, M., & Camerer, C. F. (2011). Hypothetical and real choice differentially activate common valuation areas. *Journal of Neuroscience*, *31*(2), 461-468.
- Kanwisher, N., McDermott, J., & Chun, M. M. (1997). The fusiform face area: A module in human extrastriate cortex specialized for face perception. *Journal of Neuroscience*, *17*(11), 4302-4311.
- Kaas, J. H. (2008). The evolution of the complex sensory and motor systems of the human brain. *Brain Research Bulletin*, *75*, 384-390
- Kanwisher, N., McDermott, J., & Chun, M. M. (1997). The fusiform face area: a module in human extrastriate cortex specialized for face perception. *Journal of neuroscience*, *17*(11), 4302-4311.
- Kastner, S., & Ungerleider, S. (2000). Mechanisms of visual attention in the human cortex. *Annual Review of Neuroscience*, *23*, 315-341
- Kazdin, A. E. (2000). *Encyclopedia of psychology*. Oxford, UK: Oxford University Press.
- Keller, K. (2013). *Strategic brand management* (4th ed.). Upper Saddle River, NJ: Prentice Hall.
- Keltner, D., & Gross, J. J. (1999). Functional accounts of emotions. *Cognition & Emotion*, *13*(5), 467-480.
- Kenning, P., Plassmann, H., & Ahlert, D. (2007). Applications of functional magnetic resonance imaging for market research. *Qualitative Market Research: An International Journal*, *10*(2), 135-152.
- Khalifa, S., Schon, D., Anton, J. L., & Liégeois-Chauvel, C. (2005). Brain regions involved in the recognition of happiness and sadness in music. *Neuroreport*, *16*(18), 1981-1984.

- Khan, U., DePaoli, A., & Maimaran, M. (2019). The unique role of anger among negative emotions in goal-directed decision-making. *Journal of the Association for Consumer Research*, 4(1), 76-76.
- Kim, M. J., Scult, M. A., Knodt, A. R., Radtke, S. R., d'Arbeloff, T. C., Brigidi, B. D., & Hariri, A. R. (2019). A link between childhood adversity and trait anger reflects relative activity of the amygdala and dorsolateral prefrontal cortex. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, 3(7), 644-649.
- Knutson, B., Fong, G. W., Adams, C. M., Varner, J. L., & Hommer, D. (2001). Dissociation of reward activation and outcome with event-related fMRI. *NeuroReport*, 12(17), 3683-3687.
- Knutson, B., Rick, S., Wimmer, G. E., Prelec, D., & Loewenstein, G. (2007). Neural predictors of purchases. *Neuron*, 53(1), 147-156.
- Kober, H., Barrett, L. F., Joseph, J., Bliss-Moreau, E., Londquist, K., & Wager, T. D. (2008). Functional grouping and cortical-subcortical interactions in emotion: A meta-analysis of neuroimaging studies. *NeuroImage*, 42(2), 998-1031.
- Koelsch, S., Skouras, S., & Jentschke, S. (2013). Neural correlates of emotional personality: A structural and functional magnetic resonance imaging study. *PLoS One*, 11(8), e77196. doi:10.1371/journal.pone.0077196
- Kozinets, R. (2001). Utopian enterprise: Articulating the meanings of Star Trek's culture of consumption. *Journal of Consumer Research*, 28(1), 67-88. Retrieved from www.jstor.org/stable/10.1086/321948
- Kramer, U. M., Mohammadi, B., Donamayor, N., Samii, A., & Munte, T. F. (2010). Emotional and cognitive aspects of empathy and their relation to social cognition - An fMRI study. *Brain Research*, 1311, 110-120. doi:10.1016/j.brainres.2009.11.043
- Kringelbach, M. L., & Berridge, K. C. (2012). The joyful mind. *Scientific American*, 307(2), 40-45.
- Kringelbach, M. L., O'Doherty, J., Rolls, E. T., & Andrews, C. (2003). Activation of the human orbitofrontal cortex to a liquid food stimulus is correlated with its subjective pleasantness. *Cerebral Cortex*, 13(10), 1064-1071.
- Kruschwitz, J. D., List, D., Waller, L., Rubinov, M., & Walter, H. (2015). GraphVar: A user-friendly toolbox for comprehensive graph analyses of functional brain connectivity. *Journal of Neuroscience Methods*, 245(7), 107-115.
- Kruschwitz, J. D., Waller, L., Daedelow, L. S., Walter, H., & Veer, I. M. (2018). General, crystallized and fluid intelligence are not associated with functional global network efficiency: A replication study with the Human Connectome Project 1200 dataset. *NeuroImage*, 171(1), 323-331.

- Kühn, S., Strelow, E., & Gallinat, J. (2016). Multiple “buy buttons” in the brain: Forecasting chocolate sales at point-of-sale based on functional brain activation using fMRI. *NeuroImage*, *136*, 122-128.
- Laird, A. R., Eickhoff, S. B., Li, K., Robin, D. A., Glahn, D. C., & Fox, P. T. (2009). Investigating the functional heterogeneity of the default mode network using coordinate-based meta-analytic modeling. *Journal of Neuroscience*, *29*(46), 14496-14505.
- Lantz, B. (2015). *Machine learning with R* (2nd ed.). Birmingham, UK: Packt.
- Larkin, P., Mesagno, C., Berry, J., & Spittle, M. (2018). Exploration of the perceptual-cognitive processes that contribute to in-game decision-making of Australian football umpires. *International Journal of Sports and Exercise Psychology*, *16*(2), 112-124.
- Laros, F. J., & Steenkamp, J. B. E. (2005). Emotions in consumer behavior: A hierarchical approach. *Journal of Business Research*, *58*(10), 1437-1445.
- LeDoux, J. (2000). Emotion circuits in the brain. *Annual Review of Neuroscience*, *23*(1), 155-184.
- LeDoux, J. (2015). *Anxious: Using the brain to understand and treat fear and anxiety*. New York, NY: Penguin Random House.
- Lerner, J. S., Li, Y., Valdesolo, P., & Kassam, K. S. (2015). Emotion and decision-making. *Annual Review of Psychology*, *66*, 799-823.
- Levy, I., Lazzaro, S. C., Rutledge, R. B., & Glimcher, P. W. (2011). Choice from non-choice: Predicting consumer preferences from blood oxygenation level-dependent signals obtained during passive viewing. *Journal of Neuroscience*, *31*(1), 118-125.
- Liao, W., Wu, G. R., Xu, Q., Ji, G. J., Zhang, Z., Zang, Y. F., & Lu, G. (2014). DynamicBC: A MATLAB toolbox for dynamic brain connectome analysis. *Brain Connectivity*, *4*(10), 780-790.
- Liberati, A., Altman, D. G., Tetzlaff, J., Mulrow, C., Gotzsche, P. C., Ioannidis, J. P. A., ... & Moher, D. (2009). The PRISMA Statement for reporting systematic reviews and meta-analysis of studies that evaluate health care interventions: Explanation and elaboration. *PLoS Medicine*, *6*(7), 1-28.
- Lighthall, N. R., Huettel, S. A., & Cabeza, R. (2014). Functional compensation in the ventromedial prefrontal cortex improves memory-dependent decisions in older adults. *Journal of Neuroscience*, *34*(47), 15648-15657.
- Lim, J., Kurnianingsih, Y. A., Ong, H. H., & O’Dhaniel, A. (2017). Moral judgment modulation by disgust priming via altered fronto-temporal functional connectivity. *Scientific reports*, *7*(1), 10887.

- Lin, L. Y. (2010). The relationship of consumer personality trait, brand personality and brand loyalty: An empirical study of toys and video games buyers. *Journal of Product & Brand Management*, 19(1), 4-17.
- Lindquist, K. A., Wager, T. D., Kober, H., Bliss-Moreau, E., & Barrett, L. F. (2012). The brain basis of emotion: A meta-analytic review. *Behavioral and Brain Sciences*, 35(3), 121-202. doi:10.1017/S0140525X11000446
- Lissek, S., Bradford, D. E., Alvarez, R. P., Burton, P., Espensen-Sturges, T., Reynolds, R. C., & Grillon, C. (2013). Neural substrates of classically conditioned fear-generalization in humans: a parametric fMRI study. *Social cognitive and affective neuroscience*, 9(8), 1134-1142.
- Loewenstein, G. (2001). The creative destruction of decision research. *Journal of Consumer Research*, 28(4), 499-505.
- Loewenstein, J. (2018). Surprise, recipes for surprise, and social influence. *Topics in Cognitive Science*, 11(1), 1-16.
- Luck, S. J., & Mangun, G. R. (2009). Introduction. In M. S. Gazzaniga, *The Cognitive Neuroscience* (pp. 185-186). Cambridge, MA: MIT Press.
- Luke, D. A. (2015). *A user's guide to network analysis in R*. London, UK: Springer.
- Lynch, M. (2004). Long-term potentiation and memory. *Physiological Reviews*, 84(1), 87-136.
- Maren, S. (1999). Long-term potentiation in the amygdala: A mechanism for emotional learning and memory. *Trends in Neurosciences*, 22(12), 561-567.
- Mars, R. B., Sotiropoulos, S. N., Passingham, R. E., Sallet, J., Verhagen, L., Khrapitchev, A. A., ... & Jbabdi, S. (2018). Whole brain comparative anatomy using connectivity blueprints. *eLife*, 7(1), 1-17.
- Matsunaga, M., Kawamichi, H., Koike, T., Yoshihara, K., Yoshida, Y., Takahashi, H. K., ... & Sadato, N. (2016). Structural and functional associations of the rostral anterior cingulate cortex with subjective happiness. *NeuroImage*, 134, 132-141.
- McCarthy, G., Puce, A., Gore, J. C., & Allison, T. (1997). Face-specific processing in the human fusiform gyrus. *Journal of Cognitive Neuroscience*, 9(5), 605-610.
- McClure, S. M., Li, J., Tomlin, D., Cypert, K. S., Montague, L. M., & Montague, P. R. (2004). Neural correlates of behavioral preference for culturally familiar drinks. *Neuron*, 44(2), 379-387.
- McCrae, R. R., & Costa, P. T. (1989). Rotation to maximize the construct validity of factors in the NEO Personality Inventory. *Multivariate Behavioral Research*, 24(1), 107-124.
- McCrae, R. R., & Costa, P. T. (2004). A contemplated revision of the NEO Five-Factor Inventory. *Personality and Individual Differences*, 36(3), 587-596.

- McRae, K., Ochsner, K. N., Mauss, I. B., Gabrieli, J. J., & Gross, J. J. (2008). Gender differences in emotion regulation: An fMRI study of cognitive reappraisal. *Group Processes & Intergroup Relations*, *11*(2), 143-162.
- McDonald, R. J., & White, N. M. . (1993). A triple dissociation of memory systems: Hippocampus, amygdala, and dorsal striatum. *Behavioral Neuroscience*, *107*(1), 3-22. <http://dx.doi.org/10.1037/0735-7044.107.1.3>
- McGaugh, J. (2000). Memory - A century of consolidation. *Science*, *287*(5451), 248-251.
- Mel'nikov, M. E., Petrovskii, E. D., Bezmaternykh, D. D., Kozlova, L. I., Shtark, M. B., Savelov, A. A., ... & Natarova, K. A. (2018). fMRI Response of Parietal Brain Areas to Sad Facial Stimuli in Mild Depression. *Bulletin of Experimental Biology and Medicine*, *165*(6), 741-745.
- Merz, C. J., Tabbert, K., Schweckendiek, J., Klucken, T., Vaitl, D., Stark, R., & Wolf, O. T. (2010). Investigating the impact of sex and cortisol on implicit fear conditioning with fMRI. *Psychoneuroendocrinology*, *35*(1), 33-46.
- Milad, M. R., Wright, C. I., Orr, S. P., Pitman, R. K., Quirk, G. J., & Rauch, S. L. (2007). Recall of fear extinction in humans activates the ventromedial prefrontal cortex and hippocampus in concert. *Biological psychiatry*, *62*(5), 446-454.
- Milgram, S. (1967). The small world problem. *Psychology Today*, *2*(1), 60-67.
- Milosavljevic, M., Navalpakkam, V., Koch, C., & Rangel, A. (2012). Relative visual saliency differences induce sizable bias in consumer choice. *Journal of Consumer Psychology*, *22*(1), 67–74.
- Moher, D., Cook, D. J., Eastwood, S., Olkin, I., Rennie, D., & Stroup, D. F. (2000). Improving the quality of reports of meta-analyses of randomised controlled trials: The QUOROM statement. *Oncology Research and Treatment*, *23*(6), 597-602.
- Moher, D. Liberati, A., Tetzlaff, J., Atlman, D. G., & PRISMA Group. (2008). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA Statement. *PLoS Medicine*, *6*(7), e1000097.
- Moher, D., Shamseer, L., Clarke, M., Ghersi, D., Liberati, A., Petticrew, M., ... & Stewart, L. A. (2015). Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. *Systematic Reviews*, *4*(1), 1-9.
- Moorthy S., Ratchford, B. T., & Talukdar, D. (1997). Consumer information search revisited: Theory and empirical analysis. *Journal of Consumer Research*, *23*(4), 263-277.
- Morales, A. C., & Fitzsimons, G. J. (2004). Product contagion: Changing consumer evaluations through physical contact with “disgusting” products. *Journal of Marketing Research*, *44*(2), 272-283.

- Motoki, K., & Sugiura, M. (2018). Disgust, sadness, and appraisal: Disgusted consumers dislike food more than sad ones. *Frontiers in Psychology, 9*, 1-8.
- Mowen, J. C., & Minor, M. S. (1998). *Consumer behavior* (5th ed.). Upper Saddle River, NJ: Prentice Hall.
- Muller, V. I., Cieslik, E. C., Laird, A. R., Fox, P. T., Radua, J., Mataix-Cols, D., ... & Eickhoff, S. B. (2018). Ten simple rules for neuroimaging meta-analysis. *Neuroscience and Biobehavioral Reviews, 84*, 151-161.
- Murphy, F. C., Nimmo-Smith, I., & Lawrence, A. D. (2003). Functional neuroanatomy of emotions: A meta-analysis. *Cognitive, Affective, & Behavioral Neuroscience, 3*(3), 207–233.
- Murray, E. A. (2007). The amygdala, reward and emotion. *Trends in Cognitive Sciences, 11*(11), 489-497.
- Murty, V. P., LaBar, K. S., & Adcock, R. A. (2016). Distinct medial temporal networks encode surprise during motivation by reward versus punishment. *Neurobiology of learning and memory, 134*, 55-64.
- Nahab, F. B., Hattori, N., Saad, Z. S., & Hallett, M. . (2009). Contagious yawning and the frontal lobe: An fMRI study. *Human Brain Mapping, 30*(5), 1744-1751.
- Neisser, U. (2014). *Cognitive psychology: Classic edition*. New York, NY: Psychology Press.
- Netterkoven, C., Reck, N., Goldbrunner, R., Grefkes, C., & Lucas, C. W. (2018). Short- and long-term reliability of language fMRI. *NeuroImage, 176*, 215-225.
- Newman, M. E. J., Barabasi, A. L. , & Watts, D. J. (2006). *The structure and dynamics of networks*. Princeton, NJ: Princeton University Press.
- Nguyen, P. M. (2013, April 13). Surprise. Retrieved from *Psychology Dictionary*: <https://psychologydictionary.org/surprise/>
- Noudoost, G., Chang, M.H., Steinmetz, N.A., & Moore, T. (2010). Top-down control of visual attention. *Current Opinion in Neurobiology, 20*(2), 183-190.
- Nummenmaa, L., Hirvonen, J., Parkkola, R., & Hietanen, J. K. (2008). Is emotional contagion special? An fMRI study on neural systems for affective and cognitive empathy. *Neuroimage, 43*(3), 571-580.
- Oaten, M., Stevenson, R. J., Williams, M. A., Rich, A. N., Butko, M., & Case, T. I. (2018). Moral violations and the experience of disgust and anger. *Frontiers in Behavioral Neuroscience, 12*(3), 1-14.
- Oatley, K., Keltner, D., and Jenkins, J.M. (2006). *Understanding emotions*. Malden, MA: Blackwell.

- Ochsner, K. N., Bunge, S. A., Gross, J. J., & Gabrieli, J. D. (2002). Rethinking feelings: an fMRI study of the cognitive regulation of emotion. *Journal of cognitive neuroscience*, *14*(8), 1215-1229.
- Ochsner, K. N., & Gross, J. J. (2005). The cognitive control of emotion. *Trends in cognitive sciences*, *9*(5), 242-249.
- Okada, K., & Hickok, G. (2009). Two cortical mechanisms support the integration of visual and auditory speech: A hypothesis and preliminary data. *Neuroscience Letters*, *452*(3), 219-223.
- Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing*, *17*(4), 460-469.
- Oop de Beeck, H. P., Haushofer, J., & Kanwisher, N. G. (2008). Interpreting fMRI data: Maps, modules and dimensions. *Nature Reviews Neuroscience*, *9*(2), 123-135.
- Oosterhof, N. N., Wiestler, T., Downing, P. E., & Diedrichsen, J. (2011). A comparison of volume-based and surface-based multi-voxel pattern analysis. *NeuroImage*, *56*(2), 593-600.
- Owens, M. M., Gray, J. C., Amlung, M. T., Oshri, A., Sweet, L. H., & MacKillop, J. (2017). Neuroanatomical foundations of delayed reward discounting decision-making. *NeuroImage*, *161*, 261-270.
- Oxman, A. D., & Guyatt, G. H. (1993). The science of reviewing research. *Annals of the New York Academy of Sciences*, *703*(1), 125-134.
- Papeo, L., Agostini, B., & Lingnau, A. (2019). The large-scale organization of gestures and words in the middle temporal gyrus. *Journal of Neuroscience*, 2668-18.
- Palomo-Velez, G., Tybur, J. M., & van Vugt, M. (2018). Unsustainable, unhealthy, or disgusting? Comparing different persuasive messages against meat consumption. *Journal of Environmental Psychology*, *58*(August), 63-71.
- Pardo, J. V., Pardo, P. J., Janer, K. W., & Raichle, M. E. (1990). The anterior cingulate cortex mediates processing selection in the Stroop attentional conflict paradigm. *Proceedings of the National Academy of Sciences*, *87*(1), 256-259.
- Park, M., Gutyrchik, E., Welker, L., Carl, P., Pöppel, E., Zaytseva, Y., ... & Bao, Y. (2015). Sadness is unique: neural processing of emotions in speech prosody in musicians and non-musicians. *Frontiers in human neuroscience*, *8*, 1049.
- Park, S. Q., Kahnt, T., Dogan, A., Strang, S., Fehr, E., & Tobler, P. N. (2017). A neural link between generosity and happiness. *Nature Communications*, *8*, 15964.
- Parker, W., & Stumpf, H. (1998). A validation of the Five-Factor Model of personality in academically talented youth across observers and instruments. *Personality and Individual Differences*, *25*(6), 1005-1025.

- Pereira, C. S., Teixeira, J., Figueiredo, P., Xavier, J., Castro, S. L., & Brattico, E. (2011). Music and emotions in the brain: familiarity matters. *PloS one*, 6(11), e27241.
- Pessoa, L. (2008). On the relationship between emotion and cognition. *Nature Reviews*, 9(February), 148-158.
- Petty, R. E., & Cacioppo, J. T. (1984). The elaboration likelihood model of persuasion. *Advances in Consumer Research*, 11(1), 668-672.
- Plack, C. J. (2005). Auditory perception. In K. Lamberts & R. Goldstone, *The handbook of cognition* (pp. 71-104). Thousand Oaks, CA: SAGE.
- Plassmann, H., O'Doherty, J., & Rangel, A. (2007). Orbitofrontal cortex encodes willingness to pay in everyday economic transactions. *Journal of Neuroscience*, 27(37), 9984-9988.
- Plassmann, H., Venkatraman, V., Huettel, S., & Yoon, C. (2015). Consumer neuroscience: Applications, challenges, and possible solutions. *Journal of Marketing Research*, 52(4), 427-435.
- Poldrack, R. A. (2006). Can cognitive processes be inferred from neuroimaging data? *Trends in Cognitive Sciences*, 10(2), 59-63.
- Poldrack, R. A. (2007). Region of interest analysis for fMRI. *SCAN*, 2(1), 67-70.
- Poldrack, R. A., & Gorgolewski, K. J. (2014). Making big data open: Data sharing in neuroimaging. *Nature Neuroscience*, 17(11), 1510-1517.
- Poldrack, R. A., Halchenko, Y., & Hanson, S. (2009). Decoding the large-scale structure of brain function by classifying mental states across individuals. *Psychological Science*, 20(11), 1364-1372.
- Poldrack, R. A., Mumford, J. A., & Nichols, T. (2011). *Handbook of functional MRI data analysis*. New York, NY: Cambridge University Press.
- Pool, E., Sennwald, V., Delplanque, S., Brosch, T., & Sander, D. (2016). Measuring wanting and liking from animals to humans: A systematic review. *Neuroscience & Biobehavioral Reviews*, 63, 124-142.
- Prabhakaran, V., Narayanan, K., Zhao, Z., & Gabrieli, J. D. E. (2000). Integration of diverse information in working memory within the frontal lobe. *Nature Neuroscience*, 3(1), 85-90.
- Preusschoff, K., Quartz, S.R., & Bossaerts, P. (2008). Human insula activation reflects risk prediction errors as well as risk. *Journal of Neuroscience*, 28(11), 2745-2752.
- Purcell, J., Turkeltaub, P. E., Eden, G. F., & Rapp, B. (2011). Examining the central and peripheral processes of written word production through meta-analysis. *Frontiers in Psychology*, 2, 239-255.
- Quine, W. V. (1985). States of mind. *Journal of Philosophy*, 82(1), 5-8.

- Radua, J., & Mataix-Cols, D. (2009). Voxel-based meta-analysis of grey matter changes in obsessive-compulsive disorder. *British Journal of Psychiatry, 195*(5), 393-402.
- Ramirez-Mahaluf, J. P., Perramon, J., Otal, B., Villoslada, P., & Compte, A. (2018). Subgenual anterior cingulate cortex controls sadness-induced modulations of cognitive and emotional network hubs. *Scientific reports, 8*(1), 8566.
- Rampl, L. V., Optiz, C., Welpe, I. M., & Kenning, P. (2016). The role of emotions in decision-making on employer brands: Insights from functional magnetic resonance imaging (fMRI). *Marketing Letters, 27*(2), 361-374. doi:10.1007/s11002-014-9335-9
- Ramsøy, T. Z. (2014). *Introduction to neuromarketing & consumer neuroscience*. Denmark: Neurons Inc ApS.
- Ranganath, C., Johnson, M. K., & D'Esposito, M. (2003). Prefrontal activity associated with working memory and episodic long-term memory. *Neuropsychologia, 41*(3), 378-389.
- Reed, S. K. (2013). *Cognition: Theories and applications* (9th ed.). Stamford, CT: Wadsworth Cengage Learning.
- Reevy, G. M. (2010). *Encyclopedia of emotion* (Vol. 2). Santa Barbara, CA: Greenwood Press.
- Rhodes, R. E., & Smith, N. E. (2006). Personality correlates of physical activity: A review and meta-analysis. *British Journal of Sports Medicine, 40*(12), 958-965.
- Richlan, F., Schubert, J., Mayer, R., Hutzler, F., & Kronbichler, M. (2018). Action video gaming and the brain: fMRI effects without behavioral effects in visual and verbal cognitive tasks. *Brain and Behavior, 8*(1), 1-13.
- Richter, U. H., & Arndt, F. F. (2018). Cognitive processes in the CSR decision-making process: A sensemaking perspective. *Journal of Business Ethics, 148*(3), 587-602.
- Rilling, J. K., & Sanfey, A. G. (2011). The neuroscience of social decision-making. *Annual Review of Psychology, 62*(1), 23-48.
- Rizzolatti, G., & Arbib, M. A. (1998). Language within our grasp. *Trends in neurosciences, 21*(5), 188-194.
- Rogers, E. M. (2010). *Diffusion of innovations* (4th ed.). New York, NY: The Free Press.
- Rubinov, M., & Sporns, O. (2010). Complex network measures of brain connectivity: Uses and interpretations. *NeuroImage, 52*(3), 1059-1069.
- Sætrevik, B., & Sörqvist, P. (2015). Updating working memory in aircraft noise and speech noise causes different fMRI activations. *Scandinavian Journal of Psychology, 56*(1), 1-10.
- Safety, A. G., Rilling, J. K., Aronson, J. A., Nystrom, L. E., & Cohen, J. D. (2003). The neural basis of economic decision-making in the ultimatum game. *Science, 300*(5626), 1755-1758.

- Salamone, J.D., & Correa, M. (2012). The mysterious motivational functions of mesolimbic dopamine. *Neuron*, 76(3), 470-485.
- Salimi-Khorshidi, G., Nichols, T. E., Smith, S. M., & Woolrich, M. W. (2011). Using Gaussian-process regression for meta-analytic neuroimaging inference based on sparse observations. *IEEE Transactions on Medical Imaging*, 30(7), 1401-1417.
- Salimi-Khorshidi, G., Smith, S. M., Keltner, J. R., Wager, T. D., & Nichols, T. E. (2009). Meta-analysis of neuroimaging data: A comparison of image-based and coordinate-based pooling of studies. *NeuroImage*, 45(3), 810-823.
- Schacter, D. L. (2009). Introduction. In M. S. Gazzaniga, *The cognitive neuroscience* (pp. 655-657). Cambridge, MA: MIT Press.
- Schacter, D. L., & Wagner, A. D. (1999). Medial temporal lobe activations in fMRI and PET studies of episodic encoding and retrieval. *Hippocampus*, 9(1), 7-24.
- Schaefer, M., Berens, H., Heinze, H. J., & Rotte, M. (2006). Neural correlates of culturally familiar brands of car manufacturers. *NeuroImage*, 31(2), 861-865.
- Schaefer, M., & Rotte, M. (2007). Favorite brands as cultural objects modulate reward circuit. *NeuroReport*, 18(2), 141-145.
- Schendan, H. E., Searl, M. M., Melrose, R. J., & Stern, C. E. (2003). An fMRI study of the role of the medial temporal lobe in implicit and explicit sequence learning. *Neuron*, 37(6), 103-1025.
- Scherer, K. (1997). The role of culture in emotion-antecedent appraisal. *Journal of Personality and Social Psychology*, 73(5), 902-922.
- Schienze, A., Hofler, C., Ubel, S., & Wabnegger, A. (2018). Emotion-specific nocebo effects: An fMRI study. *Brain Imaging and Behavior*, 12(1), 180-187.
- Schwienbacher, I., Fendt, M., Richardson, R., & Schnitzler, H. U. (2004). Temporary inactivation of the nucleus accumbens disrupts acquisition and expression of fear-potentiated startle in rats. *Brain Research*, 1027(1-2), 87-93.
- Scott, J. (2000). *Social Network Analysis* (2nd ed.). Thousand Oaks, CA: SAGE.
- Seung, S. (2013). *Connectome: How the brain's wiring makes us who we are*. New York, NY: Houghton Mifflin Harcourt.
- Shany, O., Singer, N., Gold, B. P., Jacoby, N., Tarrasch, R., Hendler, T., & Granot, R. (2019). Surprise-related activation in the nucleus accumbens interacts with music-induced pleasantness. *Social cognitive and affective neuroscience*, 14(4), 459-470.
- Shaw, D., & Bagozzi, R.P. (2018). The neuropsychology of consumer behavior and marketing. *Consumer Psychology Review*, 1(1), 22-40.

- Sherry, A., & Henson, R. K. (2005). Conducting and interpreting canonical correlation analysis in personality research: A user-friendly primer. *Journal of Personality Assessment*, 84(1), 37-48.
- Shimp, T. A., & Stuart, E. W. (2004). The role of disgust as an emotional mediator of advertising effects. *Journal of Advertising*, 33(1), 43-53.
- Shrager, Y., & Squire, L. R. (2009). Medial temporal lobe function and human memory. In M. S. Gazzaniga, *The cognitive neuroscience* (pp. 675-690). Cambridge, MA: MIT Press.
- Singer, T., Critchley, H. D., & Preuschoff, K. (2009). A common role of insula in feelings, empathy and uncertainty. *Trends in Cognitive Sciences*, 13(8), 334-340.
- Smidts, A., Hsu, M., Sanfey, A. G., Boksem, M. A. S., Ebstein, R. B., Huettel, S. A., ... & Yoon, C. (2014). Advancing consumer neuroscience. *Marketing Letters*, 25, 257-267. doi:10.1007/s11002-014-9306-1
- Smith, S., Nichols, T., Vidaurre, D., Winkler, A., Behrens, T., Glasser, M., ... & Miller, K. (2015). A positive-negative mode of population covariation links brain connectivity, demographics and behavior. *Nature Neuroscience*, 18(11), 1565-1567.
- Smith, S. M., & Vale, W.W. (2006). The role of the hypothalamic-pituitary-adrenal axis in neuroendocrine responses to stress. *Dialogues in Clinical Neuroscience*, 8(4), 383-395.
- Smith, S. M., Vidaurre, D., Beckmann, C. F., Glasser, M. F., Jenkinson, M., Miller, K. L., ... & Barch, D. M. (2013). Functional connectomics from resting-state fMRI. *Trends in Cognitive Sciences*, 17(12), 666-682.
- Sperling, G. (1963). A model for visual memory tasks. *Human Factors*, 5(1), 19-31.
- Sporns, O. (2011). *Networks of the brain*. Cambridge, MA: MIT Press.
- Sporns, O. (2012). *Discovering the human connectome*. Cambridge, MA: MIT Press.
- Sporns, O. (2013). The human connectome: Origins and challenges. *NeuroImage*, 80, 53-61.
- Sporns, O., Tononi, G., & Kotter, R. (2005). The human connectome: A structural description of the human brain. *PLoS Computational Biology*, 1(4), 245-251.
- Spunt, R. P., & Adolphs, R. (2019). The neuroscience of understanding the emotions of others. *Neuroscience Letters*, 693, 44-48.
- Stocco, A. (2014). Coordinate-based meta-analysis of fMRI studies in R. *The R Journal*, 6(2), 5-15.
- Strange, B. A., and Dolan, R. J. (2006). Anterior medial temporal lobe in human cognition: Memory for fear and the unexpected. *Cognitive Neuropsychiatry*, 11(3), 198-218.
- Su, L., Wan, L. C., & Wyer, R. S. Jr. (2018). The contrasting influences of incidental anger and fear on responses to a service failure. *Psychology and Marketing*, 35(9), 666-675.

- Suzuki, W. A. (2009). Comparative analysis of the cortical afferents, intrinsic projections, and interconnections of the parahippocampal region in monkeys and rats. In M. S. Gazzaniga, *The cognitive neuroscience* (pp. 659-674). Cambridge, MA: MIT Press.
- Szekely, A., Siltan, R. L., Heller, W., Miller, G. A., & Mohanty, A. (2017). Differential functional connectivity of rostral anterior cingulate cortex during emotional interference. *Social Cognitive and Affective Neuroscience, 12*(3), 476-486.
- Talukdar, T., Roman, F. J., Operskalski, J. T., Zwilling, C. E., & Barbey, A. K. (2018). Individual differences in decision-making competence revealed by multivariate fMRI. *Human Brain Mapping, 39*(1), 1-9. doi:10.1002/hbm.24032
- Thompson, B. (1984). *Canonical correlation analysis: Uses and interpretation*. Newbury, CA: Sage.
- Thompson, R., & Boden, M. (2019). State emotional clarity and attention to emotion: A naturalistic examination of their associations with each other, affect, and context. *Cognition and Emotion, 29*, 1-9. doi.org/10.1080/02699931.2019.1572597
- Tie, Y., Rigolo, L., Norton, I. H., Huang, R. Y., Wu, W., Orringer, D., ... & Golby, A. J. (2014). Defining language networks from resting-state fMRI for surgical planning—a feasibility study. *Human brain mapping, 35*(3), 1018-1030.
- Tu, L., Wang, J., Abutalebi, J., Jiang, B., Pan, X., Li, M., ... & Huang, R. (2015). Language exposure induced neuroplasticity in the bilingual brain: A follow-up fMRI study. *Cortex, 64*, 8-19.
- Tulving, E. & Murray, D. (1985). Elements of episodic memory. *Canadian Psychology, 26*(3), 235-238.
- Turkeltaub, P. E., Eden, G. F., Jones, K. M., & Zeffiro, T. A. (2002). Meta-analysis of the functional neuroanatomy of single-word reading: method and validation. *Neuroimage, 16*(3), 765-780.
- Turkeltaub, P. E., Eickhoff, S. B., Laird, A. R., Fox, M., Wiener, M., & Fox, P. (2012). Minimizing within-experiment and within-group effects in activation likelihood estimation meta-analyses. *Human brain mapping, 33*(1), 1-13.
- Tong, L. C., Karen, J. Y., Asai, K., Ertac, S., List, J. A., Nusbaum, H. C., & Hortaçsu, A. (2016). Trading experience modulates anterior insula to reduce the endowment effect. *Proceedings of the National Academy of Sciences, 113*(33), 9238-9243.
- Tusche, A., Bode, S., & Haynes, J. D. (2010). Neural responses to unattended products predict later consumer choices. *Journal of Neuroscience, 30*(23), 8024-8031.
- Tzourio-Mazoyer, N., Landeau, B., Papathanassiou, D., Crivello, F., Etard, O., Delcroix, N., ... & Joliot, M. (2002). Automated anatomical labeling of activations in SPM using a macroscopic anatomical parcellation of the MNI MRI single-subject brain. *NeuroImage, 15*(1), 273-289.

- Van der Laan, L. N., De Ridder, D. T., Viergever, M. A., & Smeets, P. A. (2012). Appearance matters: Neural correlates of food choice and packaging aesthetics. *PLoS One*, *7*(7), e41738.
- Van Essen, D. C., Smith, S. M., Barch, D. M., Behrens, T. E., Yacoub, E., Ugurbil, K., and WU-Minn HCP Consortium. (2013). The WU-Minn Human Connectome Project: An overview. *NeuroImage*, *80*, 63-79.
- Van Essen, D. C., Ugurbil, K., Auerbach, E., Barch, D., Behrens, T. E. J., Chang, A., ... & WU-Minn HCP Consortium. (2012). The Human Connectome Project: A data acquisition perspective. *NeuroImage*, *62*(4), 2222-2231.
- Vergauwe, E., Hartstra, E., Barrouillet, P., & Brass, M. (2015). Domain-general involvement of the posterior frontolateral cortex in time-based resource-sharing in working memory: An fMRI study. *NeuroImage*, *115*(15), 104-116.
- Viinikainen, M., Jääskeläinen, I. P., Alexandrov, Y., Balk, M. H., Autti, T., & Sams, M. (2010). Nonlinear relationship between emotional valence and brain activity: evidence of separate negative and positive valence dimensions. *Human brain mapping*, *31*(7), 1030-1040.
- Vigneau, M., Beaucousin, V., Herve, P. Y., Duffau, H., Crivello, F., Houde, O., ... & Tzourio-Mazoyer, N. (2006). Meta-analyzing left hemisphere language areas: phonology, semantics, and sentence processing. *Neuroimage*, *30*(4), 1414-1432.
- von Kriegstein, K., Smith, D. R., Patterson, R. D., Ives, D. T., & Griffiths, T. D. (2007). Neural representation of auditory size in the human voice and in sounds from other resonant sources. *Current Biology*, *17*(13), 1123-1128.
- Vrticka, P., Lordier, L., Bediou, B., & Sander, D. (2014). Human amygdala response to dynamic facial expressions of positive and negative surprise. *Emotion*, *14*(1), 161-169.
- Vytal, K., & Hamann, S. (2010). Neuroimaging support for discrete neural correlates of basic emotions: A voxel-based meta analysis. *Journal of Cognitive Neuroscience*, *22*(12), 2864-2885.
- Wabnegger, A., Übel, S., & Schienle, A. (2018). Voxel-based morphometry of disgust sensitivity. *Social neuroscience*, *13*(2), 241-245.
- Wagemans, J., Wichmann, F. A., & De Beek, H. O. (2005). Visual perception. In K. Lamberts & R. Goldstone, *The handbook of cognition* (pp. 3-47). Thousand Oaks, CA: SAGE.
- Wager, T. D., Jonides, J., & Reading, S. (2004). Neuroimaging studies of shifting attention: A meta-analysis. *NeuroImage*, *4*, 1679-1693.
- Wagner, T. H., Yi, T., Meeks, S., Bova, F. J., Brechner, B., Chen, Y., ... & Bouchet, L. G. (2001). A geometrically based method for automated radiosurgery planning. *International Journal of Radiation Oncology * Biology * Physics*, *48*(5), 1599-1611.

- Walter, N., Tuakchinsky, R., Pelled, A., & Nabi, R. (2019). Meta-analysis of anger and persuasion: An empirical integration of four models. *Journal of Communication, 69*(1), 73-93.
- Wang, J., Wang, X., Xia, M., Liao, X., Evans, A., & He, Y. (2015). GRETNA: A graph theoretical network analysis toolbox for imaging connectomics. *Frontiers in Human Neuroscience, 9*, 1-16.
- Wang, Y. J., & Minor, M.S. (2008). Validity, reliability, and applicability of psychophysiological techniques in marketing research. *Psychology & Marketing, 25*(2), 197-232.
- Warren, J. D., Jennings, A. R., & Griffiths, T. D. (2005). Analysis of the spectral envelope of sounds by the human brain. *NeuroImage, 24*(4), 1052-1057.
- Waskow, S., Markett, S., Montag, C., Weber, B., Trautner, P., Kramarz, V., & Reuter, M. (2016). Pay what you want! A pilot study on neural correlates of voluntary payments for music. *Frontiers in Psychology, 7*(1023), 1-10.
- Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature, 393*(6684), 440-442.
- Weiner, K. S., Natu, V. S., & Grill-Spector, K. (2018). On object selectivity and the anatomy of the human fusiform gyrus. *NeuroImage, 173*(2), 604-609.
- Wessel, J. R., Danielmeier, C., Morton, J. B., & Ullsperger, M. (2012). Surprise and error: common neuronal architecture for the processing of errors and novelty. *Journal of Neuroscience, 32*(22), 7528-7537.
- Whitfield-Gabrieli, S., & Nieto-Castanon, A. (2012). CONN: A functional connectivity toolbox for correlated and anticorrelated brain networks. *Brian Connectivity, 2*(3), 125-141.
- Whitman, R. D. (2011). *Cognition*. Hoboken, NJ: John Wiley & Sons.
- Wilde, E., Newsome, M., Bigler, E., Pertab, J., Merkely, T., Hanten, G., ... & Levin, H. S. (2011). Brain imaging correlates of verbal working memory in children following traumatic brain injury. *International Journal of Psychophysiology, 82*(1), 86-96.
- Williams, L. M., Phillips, M. L., Brammer, M. J., Skerrett, D., Lagopoulos, J., Rennie, C., ... & Gordon, E. (2001). Arousal dissociates amygdala and hippocampal fear responses: evidence from simultaneous fMRI and skin conductance recording. *Neuroimage, 14*(5), 1070-1079.
- Winecoff, A., Clithero, J. A., Carter, R. M., Bergman, S. R., Wang, L., & Huettel, S. A. (2013). Ventromedial prefrontal cortex encodes emotional value. *Journal of Neuroscience, 33*(27), 11032-11039.
- Wolfe, J. M., & Horowitz, T. S. (2004). What attributes guide the deployment of visual attention and how do they do it? *Nature Reviews Neuroscience, 5*(6), 1-7.

- Xia, M., Wang, J., & He, Y. (2013). BrainNet viewer: A network visualization tool for human brain connectomics. *PLoS One*, *8*(7), e68910.
- Yeshurun, Y., Lapid, H., Haddad, R., Gelstein, S., Arzi, A., Sela, L., ... & Sobel, N. (2009). Olfaction: From percept to molecule. In M. S. Gazzinga, *The cognitive neurosciences* (pp. 321-342). Cambridge, MA: The MIT Press.
- Ying, X., Luo, J., Chiu, C. Y., Wu, Y., Xu, Y., & Fan, J. (2018). Functional dissociation of the posterior and anterior insula in moral disgust. *Frontiers in psychology*, *9*, 860.
- Yokoyama, R., Nozawa, T., Takeuchi, H., Taki, Y., Sekiguchi, A., Nouchi, R., ... & Shinada, T. (2014). Association between gray matter volume in the caudate nucleus and financial extravagance: Findings from voxel-based morphometry. *Neuroscience Letters*, *563*, 28-32.
- Yoo, K., Rosenberg, M. D., Hsu, W., Zhang, S., Li, C. R., Scheinost, D., Constable R. T., & Chun, M. M. (2018). Connectome-based predictive modeling of attention: Comparing different functional connectivity features and prediction methods across datasets. *NeuroImage*, *167*, 11-22.
- Yoon, C., Gonzalez, R., Bechara, A., Berns, G. S., Dagher, A. A., Dube, L., ... & Spence, C. (2012). Decision neuroscience and consumer decision-making. *Marketing Letters*, *23*(2), 473-485.
- Yoon, C., Gutchess, A. H., Feinberg, F., & Polk, T. A. (2006). A functional magnetic resonance imaging study of neural dissociations between brand and person judgments. *Journal of Consumer Research*, *33*(1), 31-40.
- Yoshino, A., Okamoto, Y., Onoda, K., Yoshimura, S., Kunisato, Y., Demoto, Y., ... & Yamawaki, S. (2010). Sadness enhances the experience of pain via neural activation in the anterior cingulate cortex and amygdala: an fMRI study. *Neuroimage*, *50*(3), 1194-1201.
- Yurgelun-Todd, D. A., & Killgore, W. D. (2006). Fear-related activity in the prefrontal cortex increases with age during adolescence: a preliminary fMRI study. *Neuroscience letters*, *406*(3), 194-199.
- Zaim, A., Yi, T., & Keck, R. (2007). Feature-based classification of prostate ultrasound images using multiwavelet and kernel support vector machines. *International Joint Conference on Neural Networks* (pp. 278-281). Orlando, FL: IEEE.
- Zhang, S., & Li, C. S. (2012). Functional connectivity mapping of the human precuneus by resting state fMRI. *NeuroImage*, *59*(4), 3548-3562.

BIOGRAPHICAL SKETCH

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