中央大学博士論文

Exploring Prefrontal Activation Associated with Product Evaluation: Insights from Functional Near-Infrared Spectroscopy in Cosmetics Experience

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Summary

This thesis explores the application of consumer neuroscience to the cosmetics industry, employing functional Near-Infrared Spectroscopy (fNIRS) as a novel tool for understanding the neural mechanisms underlying consumer product evaluation. In an era where traditional marketing research often falls short in deciphering the complexities of consumer behavior, this research applies the advancements in neuroscience to bridge this gap. By focusing on the real-time evaluation of cosmetic products and employing willingness-to-pay (WTP) as an indicator of overall product value, along with analyzing incongruencies in product features, this research seeks to reveal consumer brain reactions to direct product interaction. Consequently, our aim is to provide more profound insights into the consumers' product evaluation processes and their evaluation of product features based on perceived congruency.

The first study in this thesis replicates and extends upon the methodology used by Kawabata Duncan et al. (2019), focusing on the intra-personal correlations of product evaluation. By examining the activity in the Dorsolateral Prefrontal Cortex (DLPFC), this study assesses the relationship between brain activity and consumers' willingness to pay. The objective is to validate and extend existing knowledge in consumer neuroscience, ensuring the reliability and applicability of the findings in a practical context. This study is essential in contributing to a deeper understanding of the neural dynamics consumer behavior in the cosmetics industry.

The second study focused on specific sensory evaluations, exploring how the brain processes texture congruities and incongruities in cosmetic products. This involved analyzing responses in the Inferior Frontal Gyrus (IFG) to the sensory mismatches, using semi-partial correlation analysis to find associations between texture incongruity and brain responses. This study emphasizes the importance of texture congruity in cosmetic evaluations, indicating that even slight differences in product features can significantly affect both consumer overall evaluations and the brain activations.

The findings from these studies offer insights into the consumer neuroscience. In contrast to other neuroscientific methods such as fMRI and EEG, which are challenging to use for data collection during movement or using products, fNIRS has a potential with its non-invasive approach and the flexibility in real-life settings. This research provides practical, actionable insights for the industry, aiming to enhance product development and

marketing strategies by aligning them more closely with consumer neurological responses and evaluations.

In conclusion, this thesis demonstrates the significant role of consumer neuroscience in understanding and predicting consumer behavior, paving the way for innovations in product design and marketing within the cosmetics industry and beyond.

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Abbreviations

BA	Brodmann area
BDM	Becker–DeGroot–Marschak method
Deoxy-Hb	Deoxy-hemoglobin
DLPFC	Dorsolateral prefrontal cortex
DMPFC	Dorsomedial prefrontal cortex
EDA	Electrodermal analysis
EEG	Electroencephalogram
fNIRS	Functional near-infrared spectroscopy
fMRI	Functional magnetic resonance imaging
GLM	General Linear Model
IFG	Inferior Frontal Gyrus
MNI	Montreal Neurological Institute
mPFC	Medial prefrontal cortex
NAcc	Nucleus Accumbens
OFC	Orbitofrontal prefrontal cortex
Oxy-Hb	Oxy-hemoglobin
PFC	Prefrontal cortex
TCATA	Temporal Check-All-That-Apply
TDS	Temporal Dominance of Sensation
TI	Time-intensity
vmPFC	Ventromedial prefrontal cortex
VS	Ventral Striatum
WTP	Willingness-to-pay

1. General Introduction

In industry, market research plays a crucial role as it provides valuable insights into consumer behavior and preferences, helping to determine product development and marketing strategies. This is especially important in industries like cosmetics, where the focus is not only on functional benefits but also on providing a hedonic experience to consumers.

Traditional market research methods, such as interviews, questionnaires, and self-reports have been widely used to gain consumer insights. Companies often test with prototypes to compete with their competitors in the pre-launch phase. Their aim is to collect consumers' feedback by assessing factors such as product or brand recall, liking, and purchase intent within the questionnaires. These results will be utilized in shaping the marketing and PR strategy that is essential for maximizing the potential of the product in the market.

Normally, consumers' responses are collected after the experience of products or advertisements. Therefore, one of the challenges associated with these methods is the potential for biases in the data collected (Ariely & Berns, 2010). When consumers are asked to recall their experiences from memory which is in the conscious level, there is a risk of inaccuracies by biases and ceiling effects influencing their responses.

In the early 2000s, a novel approach for studying consumer behavior appeared. This new approach is now known as Consumer Neuroscience (a.k.a. Neuromarketing) which is a combined tool and a theory from 3 disciplines: marketing, neuroscience, and psychology to better understand cognitive levels of consumers' decision making and related processes. (Ramsøy, 2015).

Enhancing our understanding of the factors and influences shaping consumers' preferences and decision-making processes through consumer neuroscience not only provides cutting-edge features of a product but also adds an extra value in developing superior products that meet consumers' expectations.

Brain measurement techniques such as functional Magnetic Resonance Imaging (fMRI), electroencephalogram (EEG), and functional Near-Infrared Spectroscopy (fNIRS) can offer deeper understandings than only from the information of subjective ratings in the

consumer neuroscience field. By obtaining consumers' neuronal activity from the brain using these non-invasive devices, the cognitive mechanisms and emotional responses (i.e., like/dislike, approach/withdrawal) to a product can be recorded directly (Rawnaque et al., 2020). In other words, different stimuli trigger associated responses in a human brain can be tracked by monitoring the real-time change in neuronal signals or in brainwaves.

One of the most employed neuroimaging methods in neuroscience is fMRI. This is attributed to its relatively high spatial resolution, even in the signals from deeper brain areas, to understand each mechanism at the neuroanatomical level (Glover, 2011; Ramachandran, 2021). Therefore, fMRI is commonly used to investigate the localization of the neural activity of consumers, while consumers perform psychological tasks (e.g., buying, choice decision making or testing a product) related to consumer behaviors (e.g., McClure et al., 2004; Knutson et al., 2007; Plassmann et al., 2010, 2007; Kühn et al., 2016).

However, several challenges arise when considering the practical application of fMRI in commercial marketing. Firstly, there is a substantial cost associated with introducing fMRI compared to not only conducting traditional marketing studies and also other neuroimaging methodologies, such as fNIRS (Alvino et al., 2020). Additionally, the measurement environment deviates significantly from real-world scenarios; for example, it does not allow for body movement in a scanner, creating an artificial and restricted setting (Ruanguttamanun, 2014). Thus, within a scanner, only limited conditions can be tested, and only specific types of stimuli can be shown while the participant is lying in the scanner. This is problematic for the manufacturer as real product experience can be difficult in the environment.

Specifically, real-world cosmetic experiences often involve natural movements and take place in various environment settings (e.g., lightings in a room, with mirror). Conducting cosmetic research within the artificial confines of an fMRI scanner may not fully capture the dynamic and diverse nature of consumer interactions with cosmetic products in everyday scenarios. This limitation could affect the generalizability of findings to understand the product evaluation, preferences, and sensory evaluation.

On the other hand, although EEG is a relatively cheaper device, the EEG signal is infamous for its high levels of noise contaminated from multiple sources such as head movement, moving posture, blinks and nearby electrical activity (Hakim & Levy, 2019).

This poses significant challenges even though EEG can record real-time responses when attempting to conduct a study in a real-world environment. The susceptibility of EEG to interference from various external factors may impact the accuracy and reliability of the recorded neural signals during consumer interactions with cosmetic experiences. Thus, while EEG offers cost advantages, its sensitivity to noise remains a notable disadvantage, particularly in capturing responses in dynamic, real-world cosmetic experiences.

In the given context, fNIRS, a relatively novel and non-invasive neuroimaging method, is well-suited to adapt to real-world settings, offering flexibility of movement with a variety of populations, e.g., infants, healthy adults, clinical patients (Pinti et al., 2018). This adaptability is particularly crucial in the context of product evaluation, where capturing real-time responses is essential, given that the consumer experience can be instantaneous at times such as make-up product use or the effects of fragrances.

In fact, there is a scarcity of studies actively employing the fNIRS methodology to investigate real-time processes in product evaluation. The additional value of fNIRS, compared to other neuroimaging methods in consumer neuroscience, is yet to be fully understood. Particularly, the potential utilization of fNIRS for real-time cosmetic evaluation methods is not yet well-established. It remains unclear in which areas of consumer research for cosmetics marketing fNIRS can be effectively used. Although the applications of fNIRS might be promising, some limitations are concerning. Nonetheless, understanding consumers through the neural mechanism via fNIRS can offer a valuable advantage to cosmetics manufacturers. This enables them to create superior products with neuroscientific evidence, providing unique benefits to consumers.

Considering these facts, the objective of this thesis is to demonstrate the potential of using fNIRS to understand the neural processes of consumers' product evaluation in the field of cosmetics industry. To achieve this aim, two studies were conducted.

The first study concentrated on assessing the neural process during real-time evaluation of cosmetic use with fNIRS, utilizing the willingness-to-pay (WTP) as an evaluation index to measure the product's perceived value. In the second study, we delved into the neural mechanisms associated with detecting incongruencies in cosmetics that impact WTP evaluations. Specifically, we investigated how consumers' expectations of a particular product feature during the actual cosmetic experience influenced WTP assessments.

To achieve the objectives presented above, the work is structured as follows: the first chapter presents the general background of consumer neuroscience and overall aim of the thesis.

The second chapter presents a brief overview of the evolution of consumer neuroscience, tracing its development from consumer psychology methods to the emergence of consumer neuroscience. It highlights studies that have played a significant role in advancing the field. The chapter also analyzed the methodological landscape, offering a summary of consumer neuroscience techniques, with a particular focus on physiological methods. A key emphasis in this section is placed on the functional Near-Infrared Spectroscopy (fNIRS) technique, a notable and novel neuroimaging method. The chapter explores the foundational principles of fNIRS, elucidates its advantages, and discusses its drawbacks in comparison to other neuroscientific methods. By examining fNIRS within the broader context of consumer neuroscience methodologies, the chapter aims to provide a comprehensive understanding of the tools and techniques employed in studying consumer behavior.

The third chapter is on the details of Study 1, which aimed to replicate findings from a prior study by Kawabata Duncan et al. (2019). This earlier study revealed the right prefrontal activation associated with WTP during a single real use of cosmetics, as assessed using fNIRS. To replicate the previous study, different cosmetics products and different population group, Caucasian females, were tested with fNIRS in the same procedure as Kawabata Duncan et al. (2019). The study explored the potential expansion of the assessment method to different categories of products and with different population groups.

The fourth chapter is on the details of Study 2 which is based on the study by Kawabata Duncan et al. (2019) and Study 1. The primary objective of this study is to explore the feasibility of a real-time, brain-based product evaluation method capable of detecting incongruencies of product features between a product and consumer's expectations. This study specifically focuses on uncovering the neural correlates of incongruency within specific cosmetic texture, which directly influencing the overall cosmetics evaluation of WTP.

And the final chapter summarizes and discusses the findings from the third and the fourth

chapter and highlights the scientific and in the real-world applications. The future perspective of implementing consumer neuroscience in the cosmetics marketing which will give significant value to science, industry, and consumers in future.

2. Background: Consumer Neuroscience Applied to the Product Evaluation

2.1. Introduction – Background of Consumer Neurosciences

Today, alongside the technological advancements in neuroscience, the application of neuroscientific principles extends beyond clinical contexts to the realm of business. This shift is driven by a growing interest in neuroscience across various fields such as neuroeconomics, neuro-aesthetics, and the dynamic fields of neuromarketing and consumer neuroscience (Ramsøy, 2015).

Notably, manufacturers are increasingly turning to neuromarketing to test their products and apply neuroscientific insights to enhance their marketing strategies. The term of 'Neuromarketing' was first proposed by Professor Ale Schmidts at the Rotterdam School of Management in 2002. He described Neuromarketing as a study of the brain and how it processes activities about consumer context such as purchase behavior which is how and why people buy (Iloka & Onyeke, 2020).

Currently, there are over a dozen companies worldwide that specialize in brain-based approaches, including the measurement of ad effects as a core component of their primary products. You can find a list of these companies on the NMSBA webpage: https://nmsba.com/neuromarketing-companies/neuromarketing-companies.

The scientific literature about consumer neuroscience published from 2004 to 2019 are examined by Alvino and colleagues in 2020. According to their analysis, almost half of the studies within this timeframe focused on examining the impact of advertisements on consumer behavior, encompassing preferences, pleasantness, and cognitive processes like attention and memory.

In the realm of consumer behavior, various aspects playing a significant role in shaping perceptions and preferences, ultimately guiding purchasing decisions in today's competitive market. Therefore, understanding the impact of advertisements is crucial for marketers. Equally important is for product manufacturers to explore the relationship between consumers and the products during product experiences.

Gathering insights from consumer responses, independent of branding effects, is valuable

for the product development cycle based on their experiences. Basically, interaction between consumers and the product occurs during the product testing phase, as illustrated in Figure 2.1-1. This stage is critical for collecting consumer insights before the product's market release and refining prototypes. Questions during this phase often relate to the product's specific functions and its hedonic qualities, including preferences, which collectively contribute to an overall assessment of the product (Bell et al., 2018). Brain imaging data offer the potential to visualize consumers' underlying preferences more accurately than standard market research methods, as they are free from biases. (Ariely & Berns, 2010).

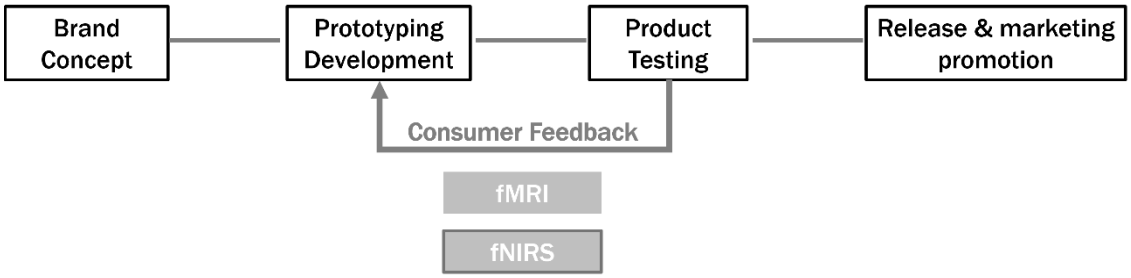

Figure 2.1-1 Product development cycle (Adopted from Ariely and Berns (2010))
Consumer feedback through neuroscience tools such as fMRI and fNIRS can refine a product before its releasing by adjustments the formulation of the cosmetic. Ultimately, this approach can add unique value to the marketing promotions.

In the next chapter, we will provide an overview of product evaluation research in consumer psychology and explore the contributions of consumer neuroscience research. As we enter the next decades of research, I believe that advancements in consumer neuroscience are expected to bring significant progress in our understanding of consumer behavior.

2.2. Overview of Product and Consumer Interaction

From the perspective of consumer science, there are various approaches of product evaluations applicable to marketing. Especially, product testing when introducing a new product to compete with existing products in the market, self-report, and behavioral measurements are commonly used to measure the consumers' responses to a product (Schmidt, 2012).

Questions are asked commonly after the experience but also possible by asking about the sensory evaluation real-time during the experience. These questions cover specific

features and sensory details, as well as overall evaluations such as preferences, purchase intentions, and willingness to pay or willingness to buy. Our introduction will begin with self-reporting methods for sensory evaluation.

2.2.1. Self-Report and Sensory Evaluation

In marketing studies, questionnaires serve as a primary tool for gathering insights into product evaluation. These surveys commonly include questions about overall evaluations, purchase intentions and hedonic responses, implying how much they desire a product with respondents using Likert scales (e.g., five-, six-, nine-point) or line scales (Civille & Carr, 2015). This questionnaire-based approach, like psychological questionnaires, facilitates a comprehensive examination of specific cosmetic attributes like fragrance, appearance, and texture. With responses collected from a diverse participant at relatively low costs, quantitative research heavily relies on self-reporting for its simplicity and informative value.

As mentioned earlier, one commonly used overall evaluation index is Willingness-to-Pay (WTP). WTP is defined as a maximum price a given consumer accepts to pay for a product or service and it is a calculation of an overall monetary value considering various factors (Lange et al., 2002; O'Brien & Viramontes, 1993). WTP scores are influenced by various factors, such as quality, security, and consumers' hedonic scores such as preferences based on gathering sensory characteristics of a product (Stefani et al., 2006). Furthermore, the determination of WTP is not just a matter of providing a price estimate; it is significantly influenced by the evaluator's past experiences. WTP requires an evaluation grounded in the individual's knowledge and prior encounters with similar products (Lichtenstein et al., 1988).

Previously, in experimental economics research, Becker, DeGroot, and Marschak's (1964) BDM procedure, employed to measure consumers' WTP for lotteries, is noteworthy. Although the BDM method was tested in a real-world field setting (Becker et al., 1964; Wertenbroch & Skiera, 2002), it faces challenges, particularly in situations where the cost of incentives is high. The feasibility of such methods may be limited, especially when dealing with high-value items, as indicated by findings suggesting potential cost implications. Notably, research results reveal no significant differences in behavior between subjects and within subjects in incentivized and non-incentivized conditions in most cases (P.-H. Lin et al., 2020). Moreover, the use of real money incentives in such studies raises ethical concerns (Hertwig & Ortmann, 2001), specifically when conducting

the study in industries. Consequently, in the current common practice, WTP is often directly assessed using methods such as open-ended questions for product valuation.

While experimental economics focuses on conducting controlled experiments to test economic theories and assumptions, behavioral economics incorporates evidence and constructs from neighboring social sciences to inform economic analysis, particularly emphasizing realistic aspects of human judgment and decision-making. The two areas are closely related, with many behavioral economists also engaging in experimental economics (Weber & Camerer, 2006).

One of the influential papers in behavioral economics is "Judgment under Uncertainty: Heuristics and Biases" by Tversky and Kahneman, originally published in Science in 1974 (Tversky & Kahneman, 1974). The insights from Kahneman and Tversky's research, along with the development of Prospect Theory by Daniel Kahneman (see Kahneman & Tversky, 2013) has been integral to the development of behavioral economics, providing a theoretical and empirical basis for understanding how cognitive biases and heuristics influence consumer decisions (Hertwig & Ortmann, 2001). This gave rise to the emergence of neuroeconomics, an interdisciplinary field integrating neuroscience, economics, and psychology. Researchers in this field employed neuroscientific tools to gain a deeper understanding of the neural mechanisms underlying economic decision-making, shedding light on how the brain processes and responds to economic choices and incentives (Loewenstein et al., 2005; Weber & Camerer, 2006). This has significantly enriched our comprehension of consumer, providing valuable insights into the current field of consumer neuroscience which will be discussed from the next chapter.

2.2.2. Temporal Sensory Evaluation

Specifically for sensory evaluation a new method called Temporal Dominance of Sensations (TDS) was proposed a decade ago (Pineau et al., 2009). This method explores the real-time dynamic, temporal dominance of sensory perceptions from the beginning to the end of the experience. Time-intensity (TI), designed to record changes in the intensity of a specific sensory attribute over time, had been proposed earlier (Lee III & Pangborn, 1986). However, TI was limited to monitoring at most two attributes (Pineau et al., 2009). Therefore, TDS aimed to overcome these limitations by selecting dominant sensations from a list of attributes (max 10), such as tastes, throughout the entire experience.

Another approach, Temporal Check-All-That-Apply (TCATA), is also noteworthy for its

ability to capture multiple attributes throughout an experience (Castura et al., 2014, 2016). This is based on CATA questions (Check-All-That-Apply) (Meyners et al., 2016) which asks panels to answer the attributes apply to the product at different time points during evaluation.

Interestingly, the initial application of TCATA was in the sensory evaluation of cosmetic creams, focusing on various attributes such as "easy to spread," "fresh," "oily," and "smooth" (Boinbaser et al., 2015). While the history of applying TCATA to temporal sensory evaluation in cosmetics is relatively recent, the potential it holds is widely acknowledged, even though specific application examples are still limited. Those sensory evaluations have a lot of information to create superior cosmetics products. Therefore, expectations are high for future developments towards their application in the development phase.

Even though, temporal sensory evaluation methods have a lot of potential for the cosmetics development, one of the challenges is the sensitive differences of cosmetics products are difficult to be assessed by consumers without any training. This is because sensory characterization of cosmetic products is regarded as difficult due to the complexity of the product and the skin condition depending on the assessors affects the evaluation (Boinbaser et al., 2015).

2.2.3. Physiological Techniques

In contrast, research in consumer science using marketing stimuli has not only relied on self-report measures but has also incorporated psychophysiological techniques introduced since the 1960s. One of the key advantages of psychophysiological measures is their ability to provide a basic, unbiased, and sensitive measure of an individual’s reaction to a stimulus. These responses are not voluntarily but autonomic reactions to a product and an advertisement as well (Stewart & Furse, 1982).

According to the review in 2008 by Wang and Minor about the psychophysiological techniques in marketing research, pupil dilation and electrodermal analysis (EDA) have been applied to predict sales and assess the effectiveness of advertisements. In the 70s, non-hemispheric brain wave analysis, hemispheric lateralization using EEG, voice pitch analysis, and eye movement analysis have been used in marketing research, and in the late 80s, cardiovascular activity such as heart rate and blood pressure, and facial muscle activity were explored by marketing researchers. Recently, neuroscientific measurements

through brain imaging analysis have been utilized to identify the brain mechanisms that underlie consumer behavior and the decision-making process (Wang & Minor, 2008).

The autonomous responses including eye-movement measured by eye-tracking, galvanic skin response (GSR) which measures changes in the electrical conductance of the skin reflecting the changes of emotional arousal level, facial-EMG which records facial muscle activities and electrocardiogram (ECG) which records electrical activity of the heart are effective to record instantaneous responses to the stimuli (e.g. advertisement), but these cannot directly reveal the underlying cognitive or emotional processes of consumer behaviors (Alvino et al., 2020).

These neurophysiological methods are known for their ability to measure responses to stimuli. These responses are primarily mediated by the autonomous nervous system. This allows for an examination of consumers' focus, arousal, attention, and withdrawal actions (Rawnaque et al., 2020). Especially, about EEG, the major limitation is the difficulty to identify the accurate origins of brain activity. This is because multiple sources within the brain can generate similar electrical potentials detectable on the scalp (Harris et al., 2018). Additionally, it is not as precise in pinpointing specific cognitive processes such as decision-making or emotional responses (Plassmann et al., 2012). This is where the integration of neuroimaging methods becomes essential to interpret these physiological measures in the context of consumer behavior.

2.2.4. Integrating Neuroimaging with Consumer Psychology

To explore the neural basis underlying purchase behavior, some researchers introduced neuroscience into the consumer psychological field as there was a hope that the neural data could help to explain what is happening inside the ‘‘black box’’ (Fugate, 2007).

Several key studies have been conducted to understand consumer behavior in the field of consumer neuroscience. For example, to explore neural correlates between subjective evaluations, such as preferences or WTP, and the associated brain areas, mainly using fMRI which can be used as evidence of the interaction between products and consumers.

fMRI is one of the most powerful tools to visualize various ranges of information processes underlying consumer behavior through its high accuracy of the localization of the brain areas (Plassmann & Karmarkar, 2015). As one of the hopes of the researchers is to predict consumer behavior from brain data, the ability to anticipate consumer

preferences and decision-making processes on a neural level holds immense potential for businesses and marketers.

Neural correlates with subjective ratings were specifically investigated with fMRI during the product evaluation or decision-making task. Here are the several foundational studies specifically in consumer neuroscience.

There are several studies that tried to forecast the market sales such as music, chocolate, and an intention to share the information based on brain activity to a product measured with fMRI (Berns & Moore, 2012; Kühn et al., 2016; Scholz et al., 2017; Tong et al., 2020). These results showed that the actual marketing sales were correlated with the activation of specific brain areas and some of them showed even higher correlations with a small number of chosen participants, suggesting that the neural information has a potential to enhance the feasibility of predicting group-level consumer behaviors.

Deppe and colleagues (2005) found that participants' favored brands activated the ventromedial prefrontal cortex (vmPFC) significantly more than other brands within the same category that were less liked.

Knutson and colleagues (2007) investigated how people decide what to buy using fMRI. They found that when people saw a product they like, the nucleus accumbens (NAcc) was activated and the medial prefrontal cortex (mPFC) was correlated with the difference between a subject's WTP and the displayed price, indicating its role in processing price information during purchase decisions. Additionally, when they saw a high price, the insula was activated.

These results suggested that these brain activities can potentially predict whether a person will decide to buy the product, even more accurately than the person's own feelings or evaluation about the overall product and the price.

Notably, two studies by Plassmann, O'Doherty, and Rangel (2007, 2010) employed WTP in the experiments with food products (Plassmann et al., 2007, 2010). In their studies, subjects bid on the right to eat snacks during the experiment and as a result, their WTP scores correlated with activity levels in the medial orbitofrontal cortex (OFC) and the dorsolateral prefrontal cortex (DLPFC). The activation of the OFC is known for its association with reward expectation (Kahnt et al., 2010). Another paper also supported

the correlation of the DLPFC with decision value to the food items measured with fMRI, suggesting the DLPFC potentially contributing to the computation of decision values. A prediction could be that the DLPFC activity may play a role in the cognitive processes involved in evaluating and comparing decision values (Sokol-Hessner et al., 2012).

While these studies observed the crucial brain areas in the economic choice decision-making process, they did not investigate the significance of the activation, such as whether higher activation in these brain areas indicates a positive valence or not (Plassmann et al., 2010). In other words, the challenge lies in the fact that WTP remains a measure of overall product evaluation, making it difficult to pinpoint the key features contributing to WTP even with neuroscientific methodology.

However, there are still many marketers only using explicit data from consumers to determine strategies, as they think self-report is enough to predict the success of a product. This is because of the advantages of self-report, owing to their low cost, relative ease of use, and flexibility to obtain information about the behavior (Kormos & Gifford, 2014). One of the meta-analyses showed that there is a high correlation between self-report and behavioral measures, however, the findings suggested a variation in the accuracy of self-report measures, with indications of slight over-reporting in some cases.

2.2.5. Schema Congruity Theory

One crucial insight mentioned in Plassmann et al., 2007 and 2010 is that the observed cognitive effort in evaluating a product may be related to the existence of prediction errors between actual outcomes and the expected value. The (in)congruency, the misalignment between expected and actual value, is supported by the Schema congruity theory. According to the theory, when a consumer desires a product, the actual product should be aligned with their expectations (Meyers-Levy & Tybout, 1989).

Schema congruity theory, proposed by Mandler (Mandler, 2014), posits that individuals process information more efficiently and favorably when it aligns with their existing mental frameworks called schemas. This theory has been applied to product evaluation in studies led by Meyers & Tybout in 1989, supporting the idea of an inverted U-shaped relation between product incongruity and the perceived product evaluation (Jhang et al., 2012; Meyers-Levy & Tybout, 1989; Noseworthy et al., 2010) (See **Table 2.2-1**. In other words, these studies suggest that it is better to avoid extremely incongruent product attributes as when the incongruity levels rise past a certain threshold, a person's ability to

make sense of a product diminishes exponentially (Meyers-Levy & Tybout, 1989). Moderate incongruity, on the other hand, is thought to be assimilated successfully into existing schemas held in memory (Mandler, 2014). The neural mechanisms underlying the detection of schema congruity remain a question for exploration.

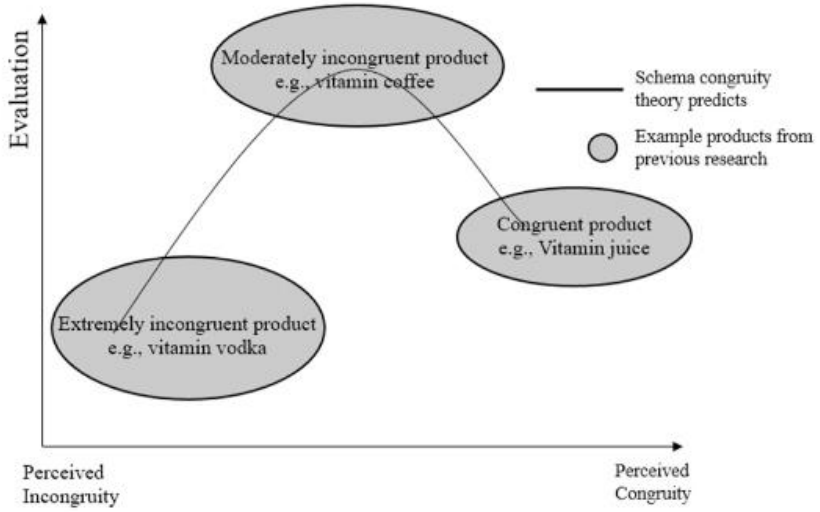

Figure 2.2-1 Difference between the theory prediction and findings of previous research (adopted from Gao et al., 2022).

While schema theory remains a valuable framework for marketing research, as evidenced by publications (Spielmann, 2016; Stumpf & Baum, 2016; Harmon-Kizer, 2017; Gao et al., 2022), the specific neural mechanisms that underlie the detection of incongruity in actual product evaluations are still not fully understood. Although several studies have utilized fMRI to explore the foundational aspects of this theory (Brod et al., 2015; van Kesteren et al., 2012), there remains a significant gap in our knowledge regarding how the brain processes and responds to information that deviates from established schemas, particularly in a marketing context. This gap highlights the need for further research to elucidate the neural responses to incongruity, enhancing our understanding of consumer behavior at a deeper, neurological level.

In the context of product evaluation during consumer experience, exploring schema incongruency has encountered limitations when employing consumer neuroscientific methods like fMRI, primarily due to the low temporal resolution within the scanner. The challenge arises from the fact that consumers initiate the evaluation process right at the beginning of the experience.

However, emerging technologies hold the promise of advancing our understanding. For instance, recording brain activation during real-time experiences, such as with fNIRS, while applying cosmetics, could provide a dynamic and in-the-moment reactions to the products. Specifically, fNIRS has a potential to explore these topics such as 1. Neural correlates with WTP during cosmetics use and 2. Neural mechanism of schema incongruency in cosmetics texture during cosmetics use. Particularly fNIRS approach can contribute valuable insights to marketing strategies and enhance our comprehension of consumer behavior to give feedback to product development.

2.2.6. Consumer Neurophysiological Methodology – Physiological Indices and Neuroscience Methods of fMRI, EEG, and fNIRS

In this thesis, the primary focus is on utilizing fNIRS. To provide a comprehensive understanding of the methodologies within consumer neuroscience, we will initially introduce physiological indices and explore general neuroscience methods before delving into an in-depth examination of fNIRS technology.

There are multiple consumer neuroscience tools employed to study consumer behavior. These tools include devices capable of measuring physiological indices and brain activity. Physiological functions and reflexes can be measured with such as electrocardiogram (ECG), blood pressure, respiration rate, and eye-tracking (Alvino et al., 2020). These measurements reflect changes in consumers' arousal and pleasantness levels, primarily based on autonomic nervous system responses to sensory stimuli such as visual, auditory, or olfactory cues (Bensafi et al., 2002).

In this thesis, the details of these physiological indices will not be discussed further as our focus of work is on neuroscientific methodology and specifically fNIRS which has a high advantage and novelty to understand consumers' neurophysiological processes.

At the point of view on how to collect signals from the brain, fMRI and fNIRS are non-invasive measurements of hemodynamic changes. fMRI detects blood-oxygen-level-dependent (BOLD) signals which reflect changes in deoxy-Hb driven by localized changes in brain blood flow and blood oxygenation, which implies underlying neuronal activity (Ogawa et al., 1990). fNIRS detects changes in the local oxy-Hb and deoxy-Hb caused by brain activity which leads to an increase in oxygen consumption (Scholkmann et al., 2014).

On the other hand, currently most EEG is non-invasive and detects directly the neuroelectric activity of the neurons and measure the electrical potentials. Many mobile systems such as EMOTIV EEG (see Aspinall et al., 2015) are developing to collect data more easily in a natural environment. Despite its high temporal resolution, as mentioned earlier, EEG has a limitation in its spatial resolution, making it challenging to precisely localize the source of brain activity. Consequently, it may not be well-suited for detecting activity in specific brain areas.

As shown in **Table 2.2-1**, fNIRS can be considered as one of the most suitable tools to investigate brain activation changes especially under a more naturalistic environment.

Table 2.2-1 Overview of neurophysiological methods

Technique		Advantages	Disadvantages	Cost	Portability
fMRI	Measures BOLD signal, blood flow and oxygenation levels in the brain.	High spatial resolustion	Low temporal resolution	High	No
		Measurable deep brain areas	Sensitive to body movement		
EEG	Recoding electrical activity generated by neurons in the brain	High temporal resolution	Low spatial resolution	Low	Yes (Portable EEG)
			Sensitive to body movement		
			Measurable only cortex areas		
fNIRS	Measures changes in blood oxygenation levels using near-infrared	Relatively high temporal resolution	Low Spatial resolution	Relatively Low	Yes (Wearable fNIRS)
		Recordable in natural body positions	Measurable only cortex areas		

2.3. fNIRS Technology

Only very recently has fNIRS been applied to consumer neuroscience research. The technology has several benefits but also some limitations.

In the late 70s, Jöbsis first demonstrated noninvasive cerebral monitoring of humans with near-infrared (NIR) light (Jöbsis, 1977). Specifically, fNIRS detects hemodynamic signal changes in the cortex regions via NIR spectrum, ranging from 650 to 950 nm. This range is particularly chosen for its effective penetration through biological tissues, including skin, skull, and brain, with minimal absorption. Notably, NIR light is minimally absorbed by water, bone, and tissue, allowing it to reach the cerebral cortex relatively unimpeded. This characteristic of NIR light, coupled with the differential absorption spectra of oxy-Hb (oxyhemoglobin) and deoxy-Hb (deoxyhemoglobin), enables fNIRS to monitor brain activity by measuring variations in blood oxygen levels.

Oxy-Hb and deoxy-Hb are the main absorbers of NIR, thus neural activity can be indirectly inferred from the changes of oxy and deoxy hemoglobin which can be indirectly quantified using conversion equations such as the modified Beer-Lambert Law (Kopton & Kenning, 2014; Gunasekara et al., 2022).

The NIR light sources, which can be either laser-emitting diodes or LED light, are placed directly on the participant's scalp. These sources emit light that penetrates the tissue in a distinctive form called "banana-shaped" path before reaching the detectors positioned on the scalp (Okada & Delpy, 2003). This unique path is due to the diffusive nature of light in biological tissues, where the emitted light spreads out and curves back towards the surface, allowing for the detection of changes in blood oxygenation levels within the brain as shown in Figure 2.3-1 (Quaresima & Ferrari, 2019). The detectors, positioned commonly a minimum of 3 cm away from the light sources, capture the NIR light after its passage through the brain tissue. This setup enables the noninvasive monitoring of cerebral blood flow changes and oxygenation by analyzing the light absorption and scattering properties of the brain tissue, employing principles akin to the Beer-Lambert law (Fukui et al., 2003).

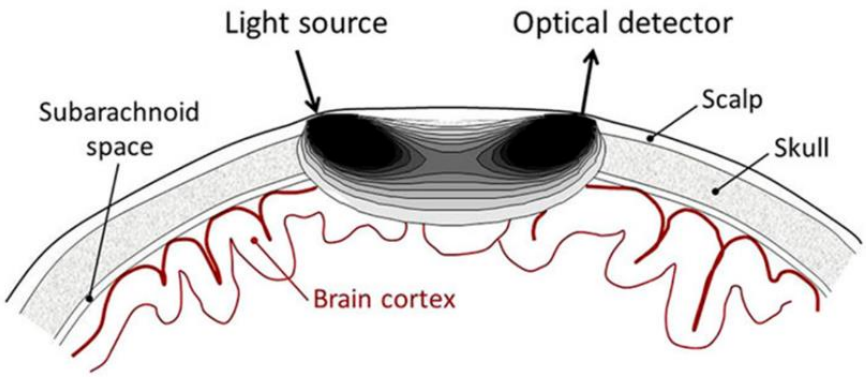

Figure 2.3-1 Schematic image of the optical region of sensitivity (banana-shaped shaded area) in non-invasive near-infrared (NIR) studies of the human brain (adopted from Quaresima & Ferrari, 2019a)

The Modified Beer-Lambert Law (MBLL) is one of the fundamental analysis method for the fNIRS signals as it was refined to account for the light scattering within biological tissues (Delpy et al., 1988). It is particularly suited for analyzing continuous wave (CW)

signals, which involve measuring the intensity of light. In this process, NIR light is sent into the tissue and the intensity of the reflected light is measured by the detectors, allowing for the assessment of cerebral blood flow and oxygenation changes (Scholkmann et al., 2014). This theoretical foundation allows researchers to extract meaningful data regarding cerebral oxygenation and blood flow changes from the fNIRS measurements.

Several methods have been developed to make it possible to map out the brain areas from fNIRS measurements to standardized brain atlases such as to the MNI standard coordinate system or to Talairach space to estimate the localization of the brain areas (Tsuzuki et al., 2007). Specifically for our consumer neuroscience study, the area of prefrontal cortex, specifically Brodmann Areas 9–12 and 46 (dorsolateral and orbitofrontal cortex), are particularly important. Thus, we focused on the PFC area in this thesis.

Next, the advantages and disadvantages of fNIRS are as follows.

2.3.1. Advantages of fNIRS Technology

Safety and comfort: fNIRS is non-invasive as its optical technique utilizes light-emitting diodes or laser diodes to measure changes in human cerebral cortex oxygenation in response to stimuli. Several systems are portable, allowing measurements in natural environments without the need for restraint, accommodating various postures (Meyerding & Mehlhose, 2020) .

Low sensitivity to body movements: fNIRS is suitable for monitoring cortical hemodynamics during motor tasks or during tasks involving even walking, which is not possible in the restrained environment of scanners. This is useful to map functional activation patterns during everyday life activities (Pinti et al., 2018).

Higher temporal resolution than fMRI: the temporal resolution of fNIRS is commonly up to 10 Hz which is relatively higher than fMRI (1–3 Hz) (Pinti et al., 2018).

Lower Cost: fNIRS instrumentation is of relatively low or moderate cost. Various systems have been developed for fNIRS including stationary but also wearable and wireless (see Scholkmann et al., 2014; Quaresima & Ferrari, 2019).

Multimodality: fNIRS is easily interfaced with other measurements. fNIRS-EEG, fNIRS-fMRI and other physiological measurements (such as heart rate, blood pressure, breathing rate), and other behavioral measurements (such as eye tracking, motion capture) can be measured together (Pinti et al., 2018).

*Applicability to Various Age Group*s: fNIRS is suitable for use across different age groups, including infants, children, and adults, making it versatile for studying consumer behavior across demographics (Pinti et al., 2018).

2.3.2. Disadvantages of fNIRS Technology

Limited Depth Penetration: fNIRS has limited penetration depth (1.5-2cm), restricting the measurement to cortical regions. Specifically, deeper brain structures involved in certain cognitive processes cannot be measured (Pinti et al., 2018).

Limited Spatial Resolution: Spatial resolution is not as precise as fMRI, making it challenging to pinpoint brain activity to specific anatomical structures (Kopton & Kenning, 2014).

Lower Temporal Resolution than EEG: the temporal resolution of fNIRS is lower than EEG (>1000 Hz) (Pinti et al., 2018).

Sensitivity to Scalp and Skull: While less sensitive to motion, fNIRS can still be affected by changes in scalp and scalp blood flow, potentially introducing noise to the data. Methods to separate this noise from the hemodynamic changes are developing (Scholkmann et al., 2014; Quaresima & Ferrari, 2019b).

Optodes placement: In case of hairy regions especially when the hair is dark, long, and/or thick, attenuate NIR light (Quaresima & Ferrari, 2019b).

Lack of standardization in data analysis: There are various adjustable parameters for preprocessing, analysis algorithms, and statistics procedures (Pinti et al., 2018; Quaresima & Ferrari, 2019b).

Researchers need to carefully consider the specific requirements of their study and the depth of brain activity they aim to investigate. However, for consumer neuroscience applications, the advantages often outweigh the disadvantages, especially in ecologically valid settings where participant movement is likely.

2.3.3. Product and Consumer Interaction with fNIRS technology

Several key studies have been conducted to explore the interaction between products and consumers and give neural evidence through actual experiences and purchase decisions using fNIRS.

Cakir and colleagues (2018) used fNIRS to discover the neural correlates of purchase decisions and found that inclusion of an understanding of budgetary constraints significantly enhanced the precision in predicting consumer purchasing behavior. This approach underscores the intricate relationship between cognitive processes and economic considerations in shaping consumer decisions. Specifically, fronto-polar and dorsomedial prefrontal cortex (DMPFC) showed significant neural activities linked to purchase decisions. This study suggested that individual differences and sensitivity to budget constraints are key factors influencing the neural mechanisms driving purchasing behavior. Thus, it should be considering both psychological and economic factors in understanding consumer decision-making processes based on their findings.

Another study by Meyerding and Mehlhose (2020) focused on the activity of the PFC and the influence of branding to enhance traditional marketing research. The study found that strong cola brands led to a higher activation in the PFC compared to weak brands during a taste test, even though the subjects received the same cola drink in every test. The results were consistent with the previous study done with fMRI by McClure and colleagues (2004) which also found that strong brands led to increased brain activation, indicating that people prefer strong brands over weak ones (McClure et al., 2004). Even though Meyerding and Mehlhose did not mention the specific activated area in the PFC, the study replicated the findings of McClure's study using fMRI, providing further support for the influence of branding and labeling on consumer preferences. Thus, this study is a good example of the application of fNIRS, building based on fMRI studies to investigate consumer preferences and decision-making processes. Also, it emphasized the fNIRS potential of understanding and predict consumers' behavior.

Notably, Kawabata Duncan et al. (2019) aimed to use fNIRS to extend the studies by

Plassman and colleagues (2007, 2010) to understand the brain activation, specifically of the DLPFC, during cosmetics experiences and the calculation of WTP. The OFC, activity in which was found in the studies by Plassmann and colleagues (2007, 2010) is located in the frontal lobes, but in the lower and frontal part near the eyes. The area is not located in a superficial region which implies that fNIRS cannot accurately measure the responses. Kawabata Duncan and colleagues (2019) more focused on the neural mechanisms of monetary product evaluation, which is more related to the PFC area especially in the DLPFC.

Kawabata Duncan et al. (2019) found a significant correlation between brain activity in the right DLPFC and WTP for high-frequency foundation users, but not for low-frequency users. This study highlights the potential of fNIRS to complement traditional consumer research, offering advantages over fMRI by enabling assessments of product value in naturalistic settings and providing individualized assessments of products and services based on neural responses.

However, the reliability of neuroscientific findings could serve as a counterargument against their validity (Kopton & Kenning, 2014). Therefore, proving the robustness of the research findings with a different group of participants and different stimulus in the same experiment scheme becomes crucial. This will increase the likelihood of practical applications, especially in fields like product development.

2.3.4. Research Outline

As mentioned earlier, several studies utilized fNIRS to investigate the interplay between products and consumers, particularly through product experiences. However, the potential remains underexplored. There is a gap in studies that comprehensively examine the neural connections between prefrontal activation and subjective ratings linked to product evaluation. Given these circumstances, this dissertation aims to provide the viability of fNIRS in product evaluation methods by validating and exploring prefrontal activation in correlation with subjective product evaluation scores.

The purpose of Study 1, described in chapter 3, were the replication and extension of the previous study by Kawabata Duncan et al. (2019). This was done by changing the group of people and altering the cosmetics product from powdery foundation to lipsticks. A positive intra-subject correlation between the right DLPFC activity measured by fNIRS and WTP scores was expected as an evaluation index.

The purpose of Study 2, described in chapter 4, was to investigate the feasibility of a real-time brain-based measurement methods with fNIRS to detect “incongruencies” between cosmetics products and consumer expectations, focusing on the texture of lipsticks.

These studies emphasize the importance of understanding the neural mechanisms underlying the interaction between consumers and products in product development. This understanding is predicted to contribute to superior product development, value creation, and enhanced marketing appeal, potentially paving the way for innovative opportunities in the cosmetics market.

3. Study1: A Willingness-to-Pay Associated Right Prefrontal Activation During a Single, Real Use of lipsticks as assessed using Functional Near-Infrared Spectroscopy

3.1. Introduction

A major goal of any consumer-oriented company is to understand consumer preferences and behavior. An important step to achieve this goal was made by the application of psychological knowledge to economic human decision making (Kahneman & Tversky, 1979). Furthermore, the application of neuroscientific approach, best exemplified by neuroimaging methods, has been applied commercially to complement traditional methods of consumer research. Several regions of the prefrontal cortex (PFC) may play a role in consumer assessment of products based on perceived benefits and cost (Solnais et al., 2013).

The expectation is that the differences in brain activity can reveal more information about consumers' responses to the products. This is because the brain derived measurements of consumer attitudes are not always the same as subjective choice preferences (Ramsøy et al., 2019), with one possible reason being that brain activity is more likely to be free of biases. This in turn may allow more accurate testing of products and prototypes even with smaller sample sizes relative to traditional self-report. Thus, applying consumer neuroscience to existing product development, marketing or selling strategies will help companies more deeply understand the decision making of their customers (Berčík et al., 2016), and therefore provide them with superior products and services.

Functional near-infrared spectroscopy (fNIRS) is a promising neuroimaging method for consumer neuroscience as it can be used to investigate brain activity in naturalistic and realistic environments with low cost. Several studies have used fNIRS to measure brain activity during consumer behavior. For example, fNIRS has been used to assess the decision-making behavior of consumers when they imagine shopping (Krampe et al., 2018) and when they evaluate specific food labels of brands using mobile fNIRS (Meyerding & Mehlhose, 2020). In terms of measuring the brain responses of consumers to products using fNIRS, one promising area is the right dorsolateral prefrontal cortex (dlPFC) (Plassmann et al., 2007). In an fMRI study, Plassmann and colleagues (2007), in

addition to the medial orbitofrontal cortex (mOFC), activity in the right dlPFC was found to correlate with willingness-to-pay (WTP), the maximum amount of money a person is willing to pay in order to obtain a product. Unlike the mOFC, activity in the dlPFC can be readily measured using fNIRS.

As a first step in developing the use of the dlPFC activity as a potential biomarker of consumer preferences and future behavior, we have investigated whether brain activity measured during a single, real use of cosmetics contains meaningful information. This first step is important because the brain activity recorded by fNIRS is noisy especially during a real-world activity like applying cosmetics. We previously observed that an intrasubject correlation between activation in a participant's right dlPFC correlated positively with their WTP for a cosmetic product (Kawabata Duncan et al., 2019). Specifically, participants applied 6 powdery foundations which varied in quality to their faces, while brain activity was measured using fNIRS. The right dlPFC is a large brain area and it is not clear which fNIRS channel corresponds to the area. Therefore, virtual registration allows the registration of fNIRS data into Montreal Neurological Institute (MNI) standard brain space (Tsuzuki et al., 2007). Once registered to MNI space it is possible to identify the channel closest to the peak identified by Plassmann and colleagues (2007). Participants' activity in this channel for the different foundations correlated with their WTP. Interestingly, this correlation was only found in higher frequency users of powdery foundation, suggesting a role of experience in evaluating the product.

DlPFC has varied roles including cognitive control, working memory, and emotion regulation (D'Esposito et al., 2000; Duncan & Owen, 2000; Golkar et al., 2012). This higher order cognitive processing can be integrated with reward signals in other areas including the mOFC to improve decision making (Hare et al., 2009). To understand why such a correlation may occur, it is helpful to understand the experience of using a cosmetic like foundation or lipstick. The dominant sensation experienced during the application of a cosmetic changes over the period of application (Boinbaser et al., 2015). Taking lipsticks as an example, at first, the user may notice the color of the lipstick, then its fragrance, softness, and finally the overall visual impression of the finished lips. This means that the evaluation of a cosmetic product like lipstick by a consumer is not instantaneous but relies on monitoring the visual effects and feelings of use which change dynamically during the application period and integrating this information to form a final unified evaluation. If the color of the lipstick is poor, there is little need to continue the evaluation, resulting in less cognitive processing and thus less activity in the right dlPFC

over the lipstick application. In other words, we expect large activation occurs when the evaluation by the subject of preferred products engages complex and analytical decision-making process following the temporal sensory perceptions during using cosmetics.

However, due to the limitation in the number of times the face can be cleansed of cosmetics the positive correlation between the right dlPFC activity and WTP observed in our previous study was based on 6 trials (Kawabata Duncan et al., 2019). Therefore, the main objective of this study was to replicate the previous study in order to rule out the possibility that the previous result was obtained through chance. In addition, we aimed to refine the method of the previous study to increase the chance that a difference in product valuation between different products can be detected. This is important because in order to be an effective biomarker of consumer preferences etc., the right dlPFC activity needs to differentiate between different products. This refinement involved the following: First, a chin rest was used to reduce head motion associated noise. Second, we used lipstick as the test product because this allowed us to manipulate both color and quality, to maximize the difference between the least preferred and most preferred products.

3.2. Method

3.2.1. Participants

Twenty-five female participants (average age: 29.6, SD: 2.9, range: 25-35) participated after giving their informed consent. All participants reported that they were able to communicate and read in Japanese and/or English. In addition, they used lipstick at least five times per week. The experiment was conducted in the Applied Cognitive Neuroscience Laboratory in Chuo University, Bunkyo-ku, Tokyo under the approval of the local ethics committees of both Chuo University and Shiseido Co., Ltd.

3.2.2. Lipstick Samples

Three levels of qualities (*High*, *mid*, and *lo*) of lipsticks were prepared in six colors for this test. The quality levels of the lipsticks were determined based on the results of the product evaluation test in the United States of America organized by Shiseido Co., Ltd. *High* and *mid* qualities of lipsticks were products of the brand *MAQuillAGE* (Shiseido Co., Ltd., Tokyo, Japan). The *lo* quality lipstick was a prototype sample which was hard and had a matt texture (see **Table 3.2-1 (A)**). Six different colors were chosen from an internal color preferences guide. Before the beginning of the test, participants were asked to place six colors of lipsticks in order of their preferences.

For each subject, their most preferred color was selected as their subject-specific "*like*" color, and the third least preferred lipstick was selected as their "*less like*" color. This was to avoid the possibility that participants could give a WTP of zero for lipsticks which were a color they did not like at all. Note that the color condition does not mean a specific color, and thus colors liked or less liked differed depending on the participants. Accordingly, in the test, participants tested six samples; two colors (*like* and *less like*) in three qualities (*High*, *mid*, and *lo*) (see **Table 3.2-1 (B)**).

Averaging the responses to "*liked*" thus represents the brain and subjective responses to "*liked*" lipsticks, regardless of the color. In the same way, averaging responses to "*less liked*" represents the brain and subjective responses to "*less liked*" lipsticks. The goal was to create a range of subjective experiences which are meaningful when averaged across participants, with the aim of maximizing the chance of finding a difference between brain responses to the lipsticks and/or a correlation between WTP and brain responses.

Table 3.2-1 Lipstick samples

(A) Lipsticks product details

Quality	Product
High (J)	MAQuillAGE Dramatic Rouge P
Mid (C)	MAQuillAGE Dramatic Rouge
Low (G)	Prototype (matt texture)

(B) Lipstick ID

Lipstick ID	
SJ = most favorite color and *high* quality	**KJ** = less liked color and *high* quality
SC = most favorite color and *mid* quality	**KC** = less liked color and *mid* quality
SG = most favorite color and *high* quality	**KG** = less liked color and *low* quality

(A) Three different lipsticks for this test are based on the product texture.

(B) The colors of S and K are selected from six colors based on each participant's color preference order. These IDs are the same for each subject, but the colors are subject-specific.

3.2.3. Experiment Design

Before the experiment began, participants received a written and verbal explanation of the experiment and that the experiment was conditional on their informed consent, where there would be no disadvantage conferred upon them should they choose to not participate. The participants were informed that they were required to apply lipstick and then type their willingness to pay for the product using a keyboard. We explained that WTP doesn't mean how much you think the price should be or how much you want it to be, but rather how the maximum amount of money you would be willing to spend to get the lipstick. In addition, we asked them to take both the quality and color into consideration. If the quality and color were such that there would be no possibility of purchase, they could respond zero for WTP. There was no upper limit for their WTP. Moreover, they were asked to use the same currency throughout the experiment.

Each lipstick was applied to only one-half of the lips (left or right) in order to reduce the number of times the lips needed to be cleansed of lipstick to minimize the burden on the delicate skin of the lips. Participants sat in front of a mirror and a PC monitor which displayed the visual information. Head motion can cause a deterioration in the signal-to-noise ratio in the fNIRS data. Since it can be challenging to hold one's head still while at the same time applying cosmetics to the face, a chin rest was used. This stabilized the head and reduced the amount of movement the participant could make with their head without undue restraint (**Figure 3.2-1)**.

In the fNIRS experimental design, one block was composed of four periods: *Rest*, *Wash*, *Trial 1*, and *Trial 2*. Before the first trial, the participant went through a single block without applying any lipstick as a practice session to get used to the process. In the *Rest* period, they kept still for 30 sec **Figure 3.2-2.** In the *Wash* period, they removed the lipsticks on their lips using a cotton pad with a cosmetic. A facial emulsion (*Elixir Superieur lift moist emulsion*, Shiseido Co., Ltd., Tokyo, Japan) was selected as a low skin irritation cosmetic to remove the lipstick.

Once the participant finished cleansing their lips, the first set of instructions were displayed on the PC monitor informing the participant which lipstick sample (SJ, SC, SG, KJ, KC, or KG)(see **Table 3.2-1** Lipstick samples (B)) they would use next and which side of the lip (left or right side) they would apply the lipstick in this session (*Instructions 1* in **Figure 3.2-2**). As it was not practical to fully counterbalance both lipstick sample and lip side (six lipsticks and two lipstick sides), the order of lipsticks, as well as the combination of lipstick sample and lip side was randomized for each participant.

After the participant received the lipstick and was ready to start, 10 seconds of baseline brain activity was recorded (*Baseline* in **Figure 3.2-2**). Then an auditory cue informed the participant that they should begin applying the lipstick and keep applying the lipstick for 30 sec (*Apply* in Figure 3.2-2) until another auditory cue informed them to stop. The second set of instructions (*Instructions 2* in **Figure 3.2-2**) were then displayed on the PC screen for the participant to press the Enter key when ready and the monitor displayed a blank white screen for 5 sec and the participant should think about how much they would be willing to pay for the lipstick they have just used (*Evaluation* in **Figure 3.2-2**). After these 5 secs elapsed, on the PC screen, the following text appeared, "Please type how

much you are willing to pay." Then they typed their WTP with a keyboard and pressed the Enter key (*Type WTP* in Figure 3.2-2). The participant was able to correct any typing mistakes they made using the Backspace key. The entry of the WTP was terminated by the participant pressing the Enter key. Therefore, a single trial comprised the lipstick application to the half side of the upper and lower lip, evaluation, and entering of WTP of a single lipstick.

In the next trial, the procedure started from *Instructions 1*. The monitor displayed a different lipstick sample from the first trial and the other side of the upper and lower lip to apply the lipstick. Then the trial proceeded in the same way as the first trial. The visual and auditory information were presented using E-Prime (E-Prime, Psychology Software Tools, Inc.).

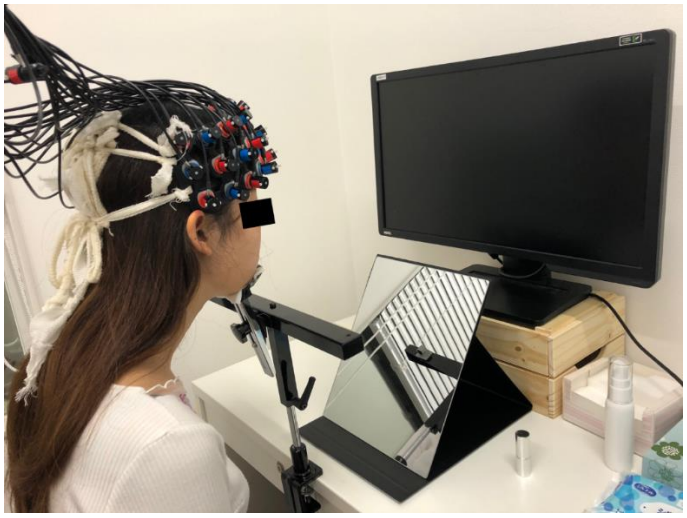

Figure 3.2-1 Experiment image

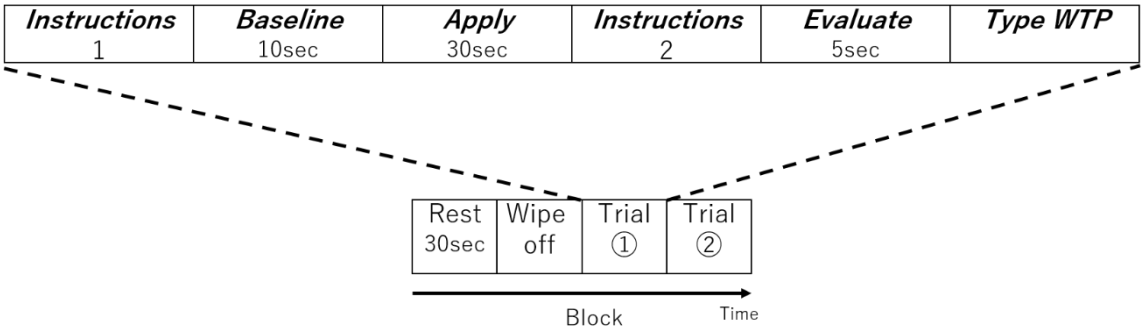

Figure 3.2-2 One block of the experimental design.

Each block consisted of two trials. The order of lipstick and the side to which they were applied were randomized.

3.2.4. fNIRS Data Acquisition

In the experiment, hemodynamic responses of the brain were measured with multichannel fNIRS optical topography system ETG-4000 (Hitachi Medical Corporation, Kashiwa, Japan) using dual wavelengths of near-infrared light (695 and 830 nm) at 10Hz sampling rate. The optical data was analyzed based on the modified Beer-Lambert Law (Cope et al., 1988). Accordingly, signals reflecting concentration changes of the oxygenated hemoglobin (oxy-Hb), and deoxygenated hemoglobin (deoxy-Hb) were obtained in units of millimolar・millimeter (mM・mm) (Maki et al., 1995). For our analysis, we focused on oxy-Hb signals since it was shown to be more reliable than the deoxy-Hb signal (Dravida et al., 2018) and only the oxy-Hb showed a correlation with behavior in our previous research (Kawabata Duncan et al., 2019)

3.2.5. Registration of fNIRS channels to MNI space

After all the testing blocks, the position of each probe was recorded using a 3D digitizer (POLHEMUS, Patriot). We used a 3 x 11 multichannel probe holder consisting of 17 illuminating and 16 detecting probes arranged alternately at an interprobe distance of 3 cm (**Figure 3.2-3A**). We set Fpz at the middle point of the lowest row the probe holder. The channel positions were registered to the MNI standard brain space (Brett et al., 2002) based on the virtual registration method (Okamoto et al., 2004; Tsuzuki et al., 2007). Simulated 52 channel positions were visualized on the reference scalp from the probe records are shown in Figure 3.2-3B. The lowest line of the probes was placed over the horizontal reference curve which includes T4, Fpz, and T3 and we set the probe holders placed along with the location of Fpz, T3, and T4 as **Figure 3.2-3B** (Tsuzuki et al., 2007). We defined the midpoint of a pair of illuminating and detecting probes as a channel location. Estimated locations were anatomically labeled using a MATLAB function which reads anatomical labeling information coded in a macroanatomical brain atlas, AAL (Tzourio-Mazoyer et al., 2002), LBPA40 (Shattuck et al., 2008), and Brodmann's atlas (Rorden & Brett, 2000).

The right dlPFC corresponds to mainly Brodmann area 9 and 46 (Rajkowska & Goldman-Rakic, 1995), with several channels potentially giving coverage. Setting the channel of interest to the same channel identified in our previous study (channel 39) may result in the analysis of data obtained from a different area of the brain, because the coverage of the channels may differ depending on various factors including head shape of the participants. In the previous test, the participants were Japanese whereas in the current experiment, the participants self-identified as Caucasian and there are significant head shape differences between the two groups (Ball et al., 2010). Therefore, we used the same method to identify the channel of interest in the current experiment as we did previously. Specifically, the channel closest to the peak ($x = 44$, $y = 44$, $z = 18$) previously reported to correlate with WTP by Plassmann and colleagues (Plassmann et al., 2007) was identified by calculating the Euclidean distance from the said peak to the MNI coordinates of each channel. The channel closest to the right dlPFC was channel 38.

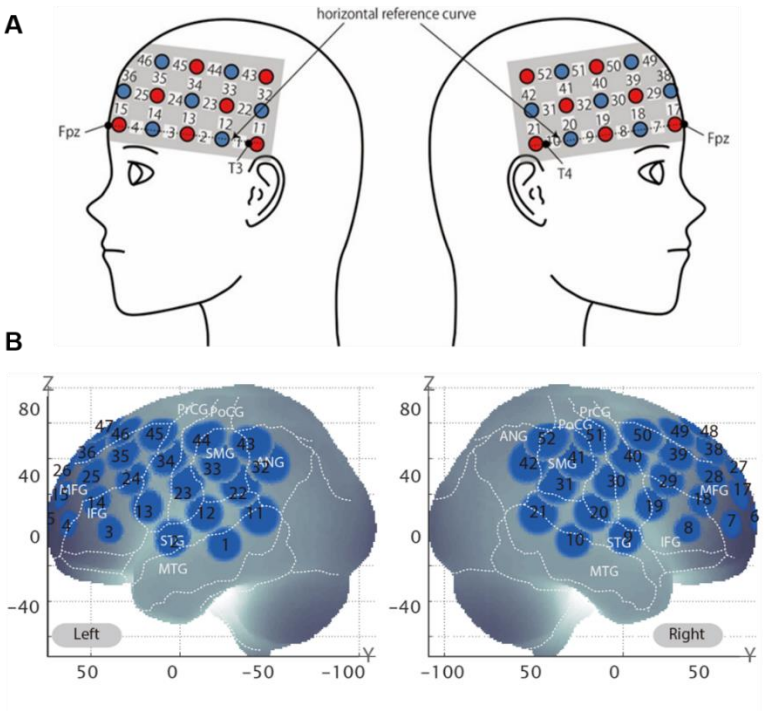

Figure 3.2-3 Virtual estimated channel positions

A. Spatial profiles of functional near infrared spectroscopy (fNIRS) channels. The upper panel shows left and right-side views of the probe arrangements are shown with fNIRS channel orientation. Detectors are indicated with dark circles, illuminators with light circles, and channels with white squares. Corresponding channel numbers are shown in black.

B. The estimated channel locations on the brain for both left and right-side views are shown. The circles indicate the spatial variability associated with the estimation exhibited in the MNI space.

3.2.6. fNIRS Data Analysis

First, channel data containing unvaried periods exceeding 10% or more of the timeline were excluded. Using Wavelet MDL detrending algorithm (Jang et al., 2009), we removed global trends due to breathing, cardiac movement, vasomotion, and other experimental artifacts. Then we preprocessed oxy-Hb time-series data for each channel of each participant using MATLAB 2007b (The MathWorks, Inc., Natick, MA, USA) with the tools from Uga and colleagues (2014) using the adaptive GLM.

Relative to averaging fNIRS data across a time interval of interest, the adaptive GLM increases statistical power by incorporating variability by using the temporal information of oxy- and deoxy-Hb signals (Uga et al., 2014). The data was regressed with a linear combination of explanatory variables. The regressors were created by convolving the hemodynamic response function (HRF) shown in Equation 1 with the boxcar function $N(\tau_{p,},t)$ (Equation 2) (Friston et al., 1998). We set 6 sec for the first peak delay, $\tau_{p,}$ as is commonly done and 16 sec for the second peak delay, τ_d, was set to 16 sec and A, the amplitude ratio between the first and second peak, was set to six sec. The first and second

derivatives were included to eliminate the influence of noise of individual data further.

Equation 1: HRF

$$h(\tau_p, t) = \frac{t^{\tau_p}\, e^{-t}}{(\tau_p)!} - \frac{t^{\tau_p + \tau_d} e^{-t}}{A(\tau_p + \tau_d)!} \quad (1)$$

Equation 2: Model waveform created by convolving the HRF and boxcar function.

$$f(\tau_p, t) = h(\tau_p, t) * N(\tau_p, t) \quad (2)$$

The regressors included in the GLM analysis were, the 30 sec *Apply*, the 5 sec *Evaluate*, and the *Type WTP* for each trial. Columns 1, 2, and 3 in **Figure 3.2-4** respectively represent the HRF of the *Apply* period and the first and second derivatives. Columns 4, 5, and 6 respectively represent the HRF of the *Evaluate* period and the first and second derivatives. Columns 7, 8, and 9 respectively represent the HRF of the *Type WTP* period and the first and second derivatives. Column 10 represents the constant. The β value is used as an estimate of the HRF prediction of the oxy-Hb signal. A total of six β values were calculated for both the *Apply* period (β_{A1}, β_{A2}, β_{A3}, β_{A4}, β_{A5}, β_{A6}) and the *Evaluate* period (β_{E1}, β_{E2}, β_{E3}, β_{E4}, β_{E5}, β_{E6}) and a single β value for the *Type WTP* period (β_{type}), giving a total of 13 β values. β_{A1} is the β for the *Apply* period of the first lipstick, β_{E1} is the β for the *Evaluate* period of the first lipstick, and so on.

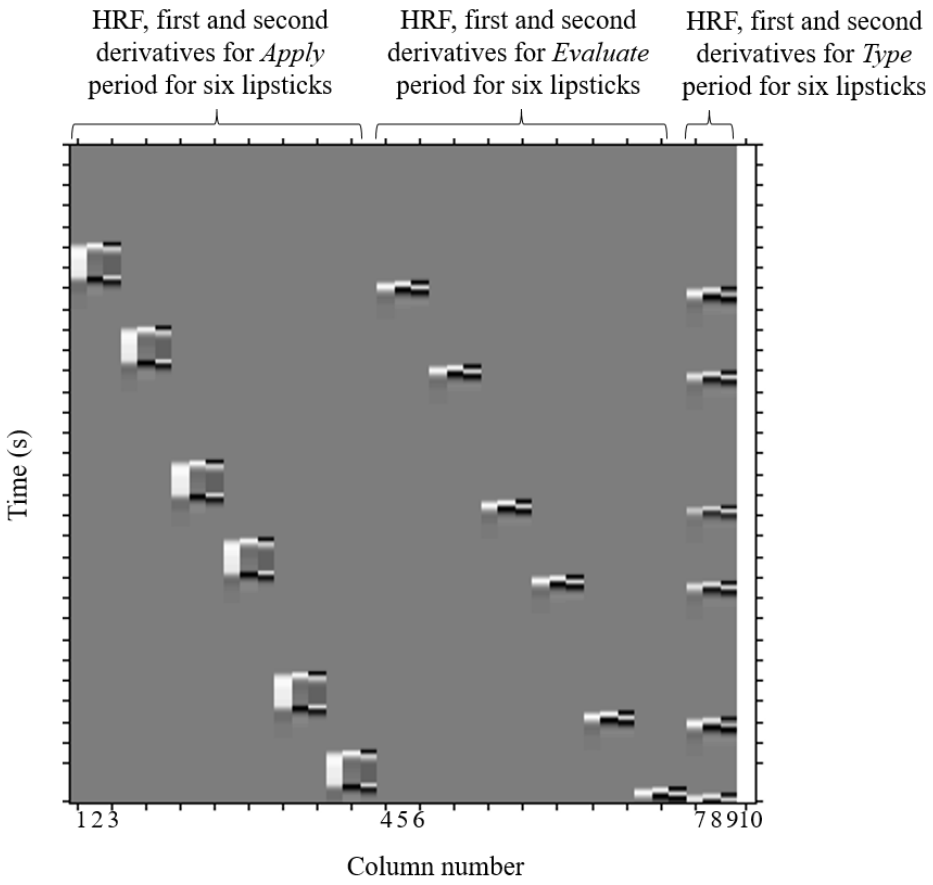

Figure 3.2-4 An example design matrix for the GLM model.

This is a design matrix from one of the participants. The design matrices of different participants will differ because of the randomization of samples and due to the fact that the duration of certain parts of the experiment differ between subjects (because the duration depends on how long it took the participant to enter their WTP then press enter, and how long it took to cleanse their lips). The first peak delay was set as τ_p= 6 s and the row number represent the time sequence with time zero being at the top. The columns designated with 1, 2, and 3 indicate the canonical hemodynamic response function (HRF) $f(\tau_p, t)$, the derivatives, and the second derivatives, respectively, for *Apply* period. There were six triplets of the regressors for application, representing six different samples. The columns designated with 4, 5, and 6 indicate those for *Evaluation* period. There were six triplets of the regressors for evaluation, representing six different samples. The column designated with 7, 8, and 9 indicates those for *Type WTP* period. The column indicated with 10 indicates the constant.

To investigate the relationship between each subject's brain activity and their WTPs, a group averaged intrasubject correlation was obtained as follows. The Spearman correlation coefficient between the *Apply* period beta values of each channel and the WTP scores for each participant was calculated. Next, the coefficient of each participant was converted into a *Z* score using Fisher's *r*-to-*z* transformation. Then, the average of *Z* score of all participants was calculated and a one sample *t*-test was conducted to determine whether each channel's mean *Z* score significantly differed from 0. The group *R* was calculated from the group *Z* score using the inverse Fisher transformation. The above process was repeated for the preprocessed deoxy-Hb time-series data, however, only the results for the oxy-Hb time-series data for our channel of interest, channel 38, are described below in **Figure 3.2-5**.

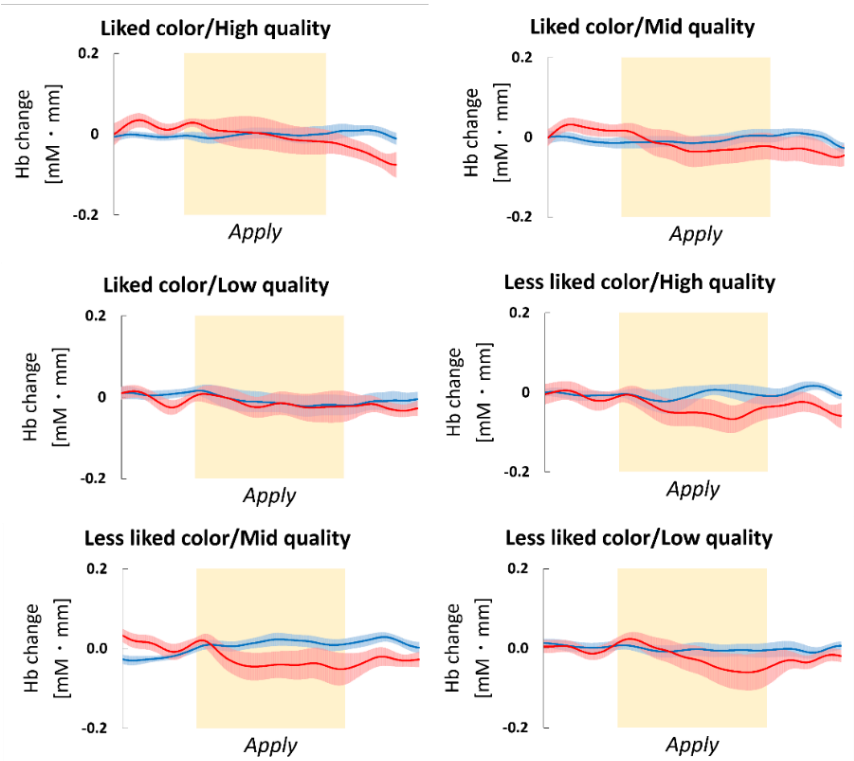

Figure 3.2-5 fNIRS Time series data of channel 38 during lipstick application

Graph of the observed time-series data for fNIRS from right hemisphere dorsolateral prefrontal cortex (dlPFC) for six lipsticks, averaged across all subjects. The red lines indicate the observed oxygenated hemoglobin (oxy-Hb) signal and the blue lines indicate deoxygenated hemoglobin (deoxy-Hb) signal. Standard errors are shown as pale red (oxy-Hb) and blue (deoxy-Hb) areas. The yellow highlighted area is the *Apply* period.

3.3. Results

3.3.1. Behavioral Performance: WTP

The average WTP for each lipstick can be seen in (**Figure 3.3-1**). The WTP data were subjected to a 2 × 3 repeated measures ANOVA with color (*like*, *less like*) and quality (hi, mid, lo) as within-subject factors. There was no main effect of color ($F_{(1,24)} = 0.019$, $p = 0.809$, $\eta^2_p = 0.001$), no main effect of quality ($F_{(1.612,38.680*)} = 0.696$, $p = 0.475$, $\eta^2_p = 0.028$) and no interaction $F_{(2,48)} = 0.047$, $p = 0.954$, $\eta^2_p = 0.002$). In other words, unexpectedly, there was no evidence that the amount of money the participants were willing to pay for the lipsticks was affected by the color or quality. *As Mauchly's test of sphericity indicated that the assumption of sphericity was violated, Greenhouse-Geisser's correction was applied.

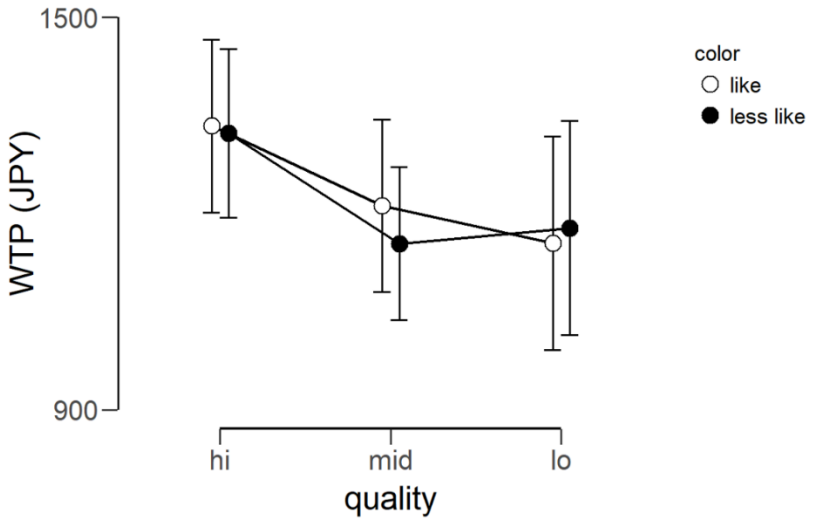

Figure 3.3-1 Average WTP (Japanese yen) for 6 lipsticks.

Graph showing the group average WTP scores of the three qualities for the two colors conditions (*less like* and *like*). Error bars represent the standard error of the mean.

3.3.2. Intra-Personal Correlation

First, we investigated whether there was any effect of the different lipsticks on activation in channel 38 (corresponding to the right dlPFC) by using a 2 x 3 repeated measures ANOVA with color (*like*, *less like*) and as quality (*hi*, *mid*, *lo*) as within subjects' factors. As can be seen in **Figure 3.3-2**, there was no main effect of color ($F_{(1,24)} = 2.12$, $p = 0.16$, $\eta^2_p = 0.081$), no main effect of quality ($F_{(2,48)} = 0.18$, $p = 0.84$, $\eta^2_p = 0.007$) and no interaction ($F_{(2,48)} = 0.29$, $p = 0.75$, $\eta^2_p = 0.012$).

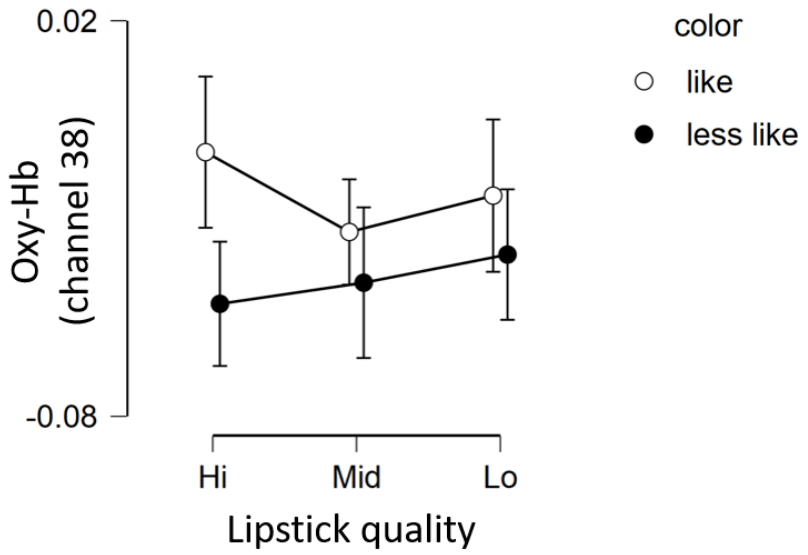

Figure 3.3-2 Brain activation in channel 38 for the 6 lipsticks.

Brain activation in channel 38 for the six lipsticks. Graph showing the group average oxy-Hb of channel 38 of the three qualities for the two colors conditions (less like and like). Error bars represent the standard error of the mean.

As described above, the coefficient for each subject's correction between their *Apply* period beta values and each WTP score was calculated and then transformed using Fisher's Z transformation into a Z score, to allow group analyses of these intrasubject correlations. Next, a Shapiro-Wilk test was used to check for violations of normality of the Z scores data (Shapiro et al., 1968). The result was statistically insignificant (p = 0.879), indicating that there was no evidence of a violation of the assumption of normality. Therefore, one sample t-test was conducted and indicated that the group Z scores for channel 38 differed significantly from 0 (mean Z = 0.24, SEM = 0.091), ($t_{(24)} = 2.5$, p = 0.03*, d = 0.65, see **Appendix A**). The group R, calculated using the inverse Fisher transformation, was 0.24. The equivalent correlations for oxy-Hb and deoxy-Hb for the remaining channels were not significant (see **Appendix A** for details).

3.4. Discussion

Incorporating neuroscientific measures into product testing may increase the ability of cosmetic product testing to predict the reaction of consumers to the product. As a first step towards this goal, it is critical to determine if meaningful brain activity can be recorded using fNIRS during a single, real use of a cosmetic. Therefore, the first objective

of the current study was to replicate the result of the previous study while using a different cosmetic product as a sample. By modifying the design of the previous study, the second objective was to identify consistent differences across subjects between lipsticks.

With respect to the first objective, we found a significant intrasubject correlation between a participant's right dlPFC activity and their WTP. In other words, we could replicate the previous study. This is important because there is concern regarding neuroimaging reproducibility (Poldrack et al., 2020) especially when sample sizes are small (Evans, 2017). The replication is particularly important in the current design because of limitations in how many times the face can be cleansed of cosmetics in a single session. This limitation means that only one trial per cosmetic, six trials in total is possible. We replicated the result in a different population with a different product strongly supports the validity of the findings. In contrast, despite optimizing the previous design, there was no consistent group difference between products in the right dlPFC activity. This is not unexpected, however, given that we were unable to find consistent group differences in WTP for the different lipsticks despite manipulating the color and quality of the lipsticks to maximize their differences. It is unclear why this manipulation did not have the expected effect.

While we replicated our previous finding (Kawabata Duncan et al., 2019), we were unable to detect any consistent group differences of brain activations across six different products. This replicates the results of our previous study. Considering the ratio of observations to variables, this may reflect an insufficient number of participants, however, there was also no difference between brain activity for only the like, hi quality and less like, lo quality samples. Moreover, despite our expectations, the manipulation of color and quality did not result in consistent group differences in WTPs. It is not clear why including like and less like conditions, would not naturally lead to like having higher average WTP. One possibility is that the manipulation of both color and quality results in a complex interaction with personal preference. In other words, a less liked color of lipstick may increase in liking depending on the quality, because the quality determines how the color will appear on the lips. Limiting the manipulation of lipsticks to only color could potentially resolve this.

The restriction in the number of trials to six is necessary due to the need to minimize the burden of removing cosmetics from the delicate skin of the face and lips. Cleansing is limited to three times per session. To increase the number of lipsticks that can be tested,

the application area of the lips was divided into left and right sides. The total number of combinations of lipsticks, lip sides, and lip order mean that full counterbalancing is not practical. There remains, therefore, the possibility that the right dlPFC correlation is an artifact of laterality. However, there are two reasons why we think that this is unlikely. First, the prefrontal cortex functional asymmetry is thought to reflect the left hemispheric involvement for verbal processing and the right hemispheric involvement for nonverbal processing (Opitz et al., 2000; Rothmayr et al., 2007), more than a location in the visual/tactile hemifield. In our study, unguided evaluation of lipstick is likely to rely heavily on nonverbal processes. Second, the current study replicates the result we found in the previous study, which seems unlikely if the current result was an artifact.

However, the underlying reason why there is a correlation between the right dlPFC activity and WTP remains unclear. Without a deeper understanding it is difficult to predict under what conditions we might expect to find the correlation and when we might not find it. Therefore, investigating this is a critical step before the correlation could be reliably implemented commercially. A further step before implementation is to determine if brain activity is superior in measuring consumer preferences and predicting behavior compared to traditional self-report.

In conclusion, we found an intrasubject correlation, during a single real use of lipstick, between participants' right dlPFC activities and their WTPs, replicating and extending our previous finding. However, as in the previous study, we were unable to find any consistent group differences in brain activations for different products. This may suggest that the use of the right dlPFC under these conditions may be best suited for a brain-based personalization or product selection process, rather than as a biomarker of all consumer preferences.

4. Study2: Right Prefrontal Activation Associated with Deviations from Expected Lipstick Texture Assessed with Functional Near-Infrared Spectroscopy

4.1. Introduction

Cosmetics companies are constantly trying to develop superior products that meet the needs, preferences, and expectations of consumers. To achieve this, they often conduct extensive sensory evaluations, which were originally used in food and beverage industries (Civille & Carr, 2015), to identify key product attributes that drive consumer satisfaction. Sensory evaluation is now applied not only in the characterization and evaluation of foods and beverages, but also in other industries, including cosmetics, to obtain data upon which informed decisions can be based (Civille & Carr, 2015). Sensory evaluation of cosmetic prototypes, especially luxury cosmetics, is essential to determine the cosmetics' quality and effectiveness.

Sensory evaluation is conventionally done using traditional subjective rating scales administered after the use of the cosmetic. However, this approach may affect the accuracy of evaluations due to biases such as peak-end, in which the highlights, lowlights, and end sensations of an experience bias one's recollections of how that experience felt (Higgins & Altman, 2008; Ares et al., 2013; Scheibehenne & Coppin, 2020). To avoid such biases, real-time sensory evaluation methods for measuring temporal changes in sensations have been developed; they include time-intensity (TI) evaluation (Neilson, 1957; Lee III & Pangborn, 1986) and TDS (temporal dominance of sensation) (Pineau et al., 2009). As study participants who test cosmetic products are required to be sensitive to relatively small effects of the test product, the act of reporting their own perceptions and sensations may interfere with their natural product experience, potentially producing misleading results (Civille & Carr, 2015).

A promising alternative approach may be to use neuroimaging techniques, which offer a unique opportunity to gain deeper insights into consumers' sensory experiences without interfering with real-life product usage. For instance, functional Near Infrared Spectroscopy (fNIRS) has the potential to evaluate consumers' experiences of cosmetic products during their real-time use (Kawabata Duncan et al., 2019; Hirabayashi et al.,

2021). fNIRS is a non-invasive neuroimaging technique that uses near-infrared light to measure hemodynamic signals reflecting changes in hemoglobin concentrations in the brain. It is well-suited for measuring brain activation during real-world tasks and has been used successfully in previous sensory studies such as taste (Okamoto & Dan, 2007; Hu et al., 2014), flavor (Okamoto et al., 2006; Hasegawa et al., 2013), and tactile stimuli (Hong et al., 2017).

Our team has reported that information regarding consumers' monetary evaluations of different cosmetics can be obtained using fNIRS (Kawabata Duncan et al., 2019; Hirabayashi et al., 2021). Our previous studies suggested that the right dorsolateral prefrontal cortex (DLPFC) could be developed as a biomarker for consumer preferences as there was an intra-subject correlation between the right DLPFC activations of participants and their Willingness-To-Pay (WTP) scores during a single, real-time use of cosmetic products. Nonetheless, despite the utility of such an overall evaluation of the cosmetic experience, it is still essential to understand what specific features influence WTP.

One such feature is the texture of cosmetics. In particular, understanding whether or not specific aspects of a product's texture meet or fail to meet consumers' expectations is important in order to optimize product formulations. This process is theoretically described by the schema congruity theory, which posits that the similarity between a product and a broader product category schema affects the processing of incoming sensory information and the resultant evaluation for stimuli such as beverages and scents (Meyers-Levy & Tybout, 1989; Bosmans, 2006; Noseworthy et al., 2014; Lanseng & Sivertsen, 2019). According to this theory, consumers prefer products that align with their existing schemas which are generated based on their memories of previous experiences and which in turn forms their expectations regarding products and brands (Halkias, 2015; Eklund & Helmefalk, 2021). Another study highlighted the importance of understanding consumers' cognitive processes for shaping consumer perceptions and decisions (Mandler, 2014).

In the context of consumer experience of cosmetics such as lipstick, consumers are likely to have formed a schema which incorporates properties such as softness. Excessive deviations from this schema, such as lipsticks which are too soft or too hard, are likely to result in a negative experience and evaluation. While the schema congruity theory provides a robust framework for understanding consumers' evaluations of products, the

neural mechanisms underlying these cognitive processes during actual consumer experiences remain unclear. This gap highlights the need for further research to understand how consumers' brains process sensory information in line with or in opposition to their existing schemas, thus influencing their product evaluations.

Thus, the aim of the present study was to investigate the feasibility of a real-time brain-based product evaluation method which detects the incongruency of a product with a consumer's expectations. We focused on lipstick as it is recognized as one of the iconic symbols of luxury cosmetic products (Gerstell et al., 2020) and softness because this is one of the key determinants of the consumer experience with lipstick. To measure the incongruency of six lipsticks which differed in softness, participants evaluated their perception of the softness on a visual analogue scale (VAS; from -50 to 50) ranging from *too soft* to *too hard*, resulting in an incongruency score. fNIRS was used to measure the real-time brain activity covering the frontal areas, including the medial Prefrontal Cortex (mPFC), DLPFC, and inferior frontal gyrus (IFG), which we hypothesized, based on previous studies, may be involved in the detection of incongruency (Yeon et al., 2017; Zhang et al., 2008; van Kesteren et al., 2013; Brod et al., 2015; Lin et al., 2018). Due to limitations of the fNIRS system, the anterior cingulate cortex (ACC) was not included. Finally, the relationship between the fNIRS data and incongruency scores was examined using semi-partial intra-subject correlations.

4.2. Methods

4.2.1. Participants

Thirty healthy, right-handed, Japanese female participants (average age: 29.8 years, SD: 3.7, range: 25-35) who did not have any dermatological conditions resulting in their skin, including the lips, being sensitive or delicate, were recruited via a recruiting company. All participants were native Japanese speakers with no history of neurological, psychiatric, or cardiac disorders. Before the experiment, informed consent was obtained from all participants. They had normal or corrected-to-normal vision and normal color vision. Handedness was assessed by means of the Edinburgh Inventory (Oldfield, 1971). This study was performed in accordance with the principles in the Declaration of Helsinki and approved by the ethical committee at the Shiseido Global Center and Chuo University. As our previous studies only found a relationship between brain activity and subjective ratings in high-frequency cosmetic users (Kawabata Duncan et al., 2019; Hirabayashi et al., 2021), all participants habitually used lipstick at least five times per week and they all preferred to use the common lipstick color called *MAQuillAGE Dramatic Rouge*

(Shiseido Co., Ltd., Tokyo, Japan). Their familiarity with lipstick also helped ensure compliance with the experiment instructions. This is a mid-price and popular product which helped facilitate participant recruitment. We conducted this experiment at Chuo University.

4.2.2. Lipstick Samples

Six lipsticks with different levels of softness, including one commercially available at the time of the study and five prototype samples, were prepared **(Table 4.2-1**). The levels of lipstick softness were determined based on the measured physical property values of lipstick products to be balanced in a wide range from too soft to too hard. To avoid the possibility that participants would give a WTP of zero for any given lipstick based solely on their color preferences, the colors of all lipsticks were chosen from an internal color preference guide and fixed for each participant. The physical properties of the lipsticks were measured with a FUDOH Rheometer (Rheotech Co., Ltd., Tokyo, Japan). All lipsticks were presented in the same plain packages.

Table 4.2-1 Details of lipstick samples

Lipstick ID	Hardness	Softness level	Details
P	5	Very soft	Prototype 1
Q	11		*MAQuillAGE Dramatic Rouge*
R	14	↕	Prototype 2
S	42		Prototype 3
T	95		Prototype 4
U	134	Very hard	Prototype 5

Note: The six different lipsticks used in the experiment were selected based on their measured hardness. Lipstick Q was chosen as the product with the preferred softness based on an internal survey. The remaining lipsticks varied in texture, ranging from too soft to too hard. The color of the lipsticks remained consistent for each variant.

4.2.3. Experiment Design

For the fNIRS experimental design, one block was composed of four periods: Rest, Wipe off, Trial 1, and Trial 2. During the rest period, participants kept still for 30 sec (**Figure 4.2-1**). During the wipe off period, they removed the lipstick using a cotton pad with a facial emulsion (*Elixir Superieur lift moist emulsion*, Shiseido Co., Ltd., Tokyo, Japan), which was selected due to its low risk of skin irritation. Participants sat in front of a mirror and a PC monitor that displayed the visual information. A chin rest was used to reduce fNIRS noise associated with motion artifacts. Visual and auditory information was presented using E-Prime (E-Prime 2.0, Psychology Software Tools, Inc., Sharpsburg, PA, USA).

Once the participant finished removing the lipstick, a set of instructions was displayed on the PC monitor informing the participant which lipstick sample (P, Q, R, S, T, or U) they would use next and which side of the lip (left or right) they would apply the lipstick to in this trial. Each lipstick was applied to only one half of the lips to reduce the burden on the delicate skin of the lips. After the participant received the lipstick and was ready to start, 10 s of baseline brain activity was recorded as will be described later. Then, an auditory cue informed the participant that they should begin applying the lipstick and keep applying the lipstick for 30 s until another auditory cue informed them to stop.

Another set of instructions was then displayed on the PC screen which indicated that during the next 5 s, the “Evaluate” period, the participant should think about how much they would like to pay for the lipstick they had just used based on their perception of its softness. Once this 5 s had elapsed, they input their WTP using the keyboard and pressed the Enter key. Next, the VAS appeared on the display and the participant input their perception of the lipstick’s softness, from -50 to 50, using a mouse. The scale was presented without the values shown. The left end was labeled “too soft; -50”, the right end was labeled “too hard; 50”, and, hence, the zero point was optimal. After the VAS rating, the participant clicked the button to end the trial. The next trial then began, and the procedure was repeated. Participants repeated this for 3 blocks, and they tried a total of six lipsticks. The absolute value of the rated perceived softness was used as the incongruency score.

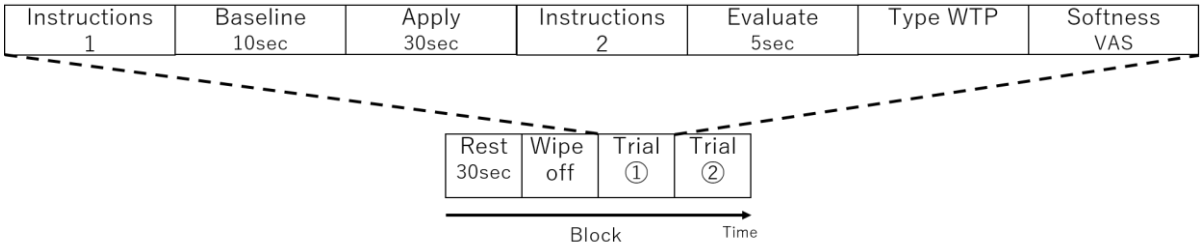

Figure 4.2-1 Experimental design (1 block)

Each block consisted of two trials. The order of lipsticks and the side to which they were applied were randomized.

4.2.4. fNIRS Data Acquisition

In the experiment, hemodynamic responses of the brain were measured with a multichannel fNIRS optical topography system ETG-4000 (Hitachi Medical Corporation, Kashiwa, Japan) using dual wavelengths of near-infrared light (695 and 830 nm) at a 10 Hz sampling rate. The optical data was analyzed based on the modified Beer-Lambert Law (Cope et al., 1988). Accordingly, signals reflecting concentration changes of the oxygenated hemoglobin (oxy-Hb) and deoxygenated hemoglobin (deoxy-Hb) were obtained in units of millimolar・millimeter (mM・mm) (Maki et al., 1995). For our analysis, we focused on the oxy-Hb signal because it has been shown to be more reliable than the deoxy-Hb signal (Dravida et al., 2018) and only the oxy-Hb signal showed a correlation with behavior in our previous research (Kawabata Duncan et al., 2019; Hirabayashi et al., 2021). We used a 3 × 11 multichannel probe holder consisting of 17 illuminating and 16 detecting probes arranged alternately at an inter-probe distance of 3 cm, producing a total of 52 channel positions for measurement (**Figure 4.2-2A**). The probe was mounted using the international 10–20 system as a reference point. First, the multichannel probe holder was placed such that the detector in the middle of the lowest row corresponded to the Fpz. Then, the illuminators and detectors in the lowest row were matched to the horizontal reference curve, which was determined by a straight line connecting T3-Fpz-T4 (Klem et al., 1999; Jurcak et al., 2007).

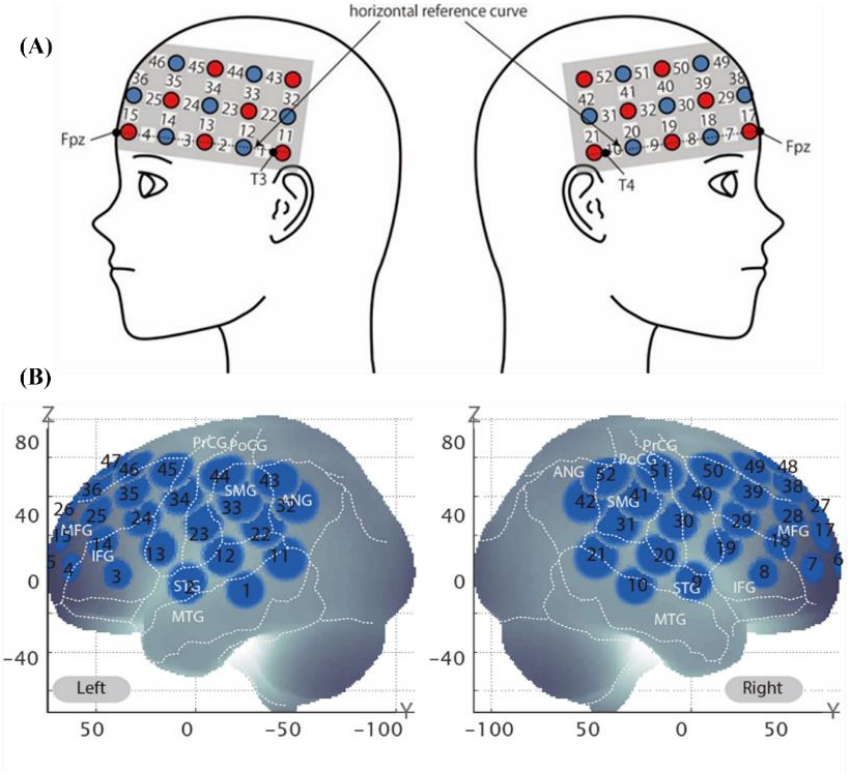

Figure 4.2-2 Virtually estimated channel positions

(A) Spatial profiles of functional near infrared spectroscopy (fNIRS) channels. This figure shows left- and right-side views of the probe arrangements with fNIRS channel orientation. Detectors are indicated with blue circles, illuminators with red circles, and channels with white squares.

(B) The estimated channel locations on the brain for both left and right-side views are shown. Corresponding channel numbers are shown in black. The circles indicate the spatial variability associated with the estimation exhibited in Montreal Neurological Institute (MNI) space.

Registration of fNIRS channels to MNI space

After fNIRS measurements, the location of all the optodes and landmarks, such as the nasion, inion, Cz, and bilateral preauricular reference points, were acquired using the Polhemus Patriot digitizer (Polhemus, Colchester, VT, USA). We employed probabilistic registration to register fNIRS data to MNI (Montreal Neurological Institute) standard brain space (Tsuzuki et al., 2007; Tsuzuki & Dan, 2014). The spatial registration data were registered with macro-anatomical labeling (Okamoto et al., 2004; Okamoto & Dan, 2005) in reference to Brodmann's atlas (BA) (Rorden & Brett, 2000) and secondarily to the macro-anatomical labeling in LPBA40 (Shattuck et al., 2008). Data for three participants' data were removed because of positional errors in probe placement.

4.2.5. fNIRS Data Analysis

For the first-level analysis, oxy-Hb time series data were analyzed with in-house MATLAB analysis tools developed in the Applied Cognitive Neuroscience Laboratory at Chuo University (available upon request). First, we used Platform for Optical Topography Analysis Tools (POTATo) (Sutoko et al., 2016) for data preprocessing. The individual oxy-Hb time series data of each of the 52 channels were preprocessed with a first-degree polynomial fitting and high-pass filter using cut-off frequencies of 0.01 Hz to remove baseline drift and a 0.8 Hz low-pass filter to remove heartbeat and pulse noise. Channels with signal fluctuations of 10% or less were considered to have poor measurement quality and were excluded from the analysis. Then, wavelet minimum description length (Wavelet-MDL) was applied to remove the effects of measurement noise, such as respiration and heart motion, from the remaining channels (Jang et al., 2009). After preprocessing, we conducted general linear model (GLM) analysis with regression of HRF on the oxy-Hb time series data from each channel for each subject. Basis functions used for GLM analysis were generated from the HRFs $\boldsymbol{h(\tau_p, t)}$ (Equation 1; Friston et al.,
1998).

$$\boldsymbol{h(\tau_p, t)} = \frac{t^{\tau_p} e^{-t}}{(\tau_p)!} - \frac{t^{\tau_p+\tau_d} e^{-t}}{A(\tau_p+\tau_d)!} \quad (1)$$

Where *t* represents a point in the time series, $\boldsymbol{\tau_p}$ represents the first peak delay, set as 6 s, and $\boldsymbol{\tau_d}$ represents the second peak delay, set as 16 s. *A*, which is the amplitude ratio between the first and second peaks, was set to 6 s as is commonly done in typical fMRI studies. The first and second derivatives were included to further eliminate the influence of noise of individual data.

Basis functions $\boldsymbol{f(\tau_p, t)}$ were generated by convolving the HRF $\boldsymbol{h(\tau_p, t)}$ with a

boxcar function $\boldsymbol{u(t)}$ (Equation 2),

$$\boldsymbol{f(\tau_p, t) = h(\tau_p, t) \otimes u(t)} \quad (2)$$

where the symbol $\otimes$ denotes convolution integral. The basic functions were used to compose each regressor described as follows. The regressors included in the GLM analysis were, thirty sec Apply, five sec Evaluate, Type WTP, and Rate Softness (VAS) for each trial. The β value is used as an estimate of the HRF prediction of the oxy-Hb signal. A total of six β values corresponding to lipstick samples P, Q, R, S, T, and U were calculated for both the Apply period, as β_{AP}, β_{AQ}, β_{AR}, β_{AS}, β_{AT}, and $\beta_{AU,}$ and the Evaluate period, as β_{EP}, β_{EQ}, β_{ER}, β_{ES}, β_{ET}, and β_{EU}. Single β values were obtained for the Type WTP and Rate Softness (VAS) periods combined as β_{type}. Consequently, a total of thirteen β values were obtained. **Figure 4.3-4** shows the observed hemodynamic responses and the predicted responses, which were determined by combining regressors adjusted for each participant with personalized adaptive GLMs.

Next, we calculated the Spearman correlation coefficient for each of the 52 channels of each participant between the incongruency scores and the apply period of β values from β_{AP} to β_{AU} in order to investigate whether there was a significant intrasubject correlation. The inclusion of the incongruency scores differs compared to our previous experimental designs (Kawabata Duncan et al., 2019; Hirabayashi et al., 2021). In this study, we specifically aimed to investigate the intra-subject correlation between the incongruency scores for products P to U, and β_{AP} to β_{AU}. However, we also needed to consider the presence of a third variable, WTP, in order to ensure that the correlations were explained as the association between two random variables after eliminating the effect of the other random variables (Kim, 2015).Therefore, we utilized semi-partial correlation (Tabachnick & Fidell, 2014), a type of statistical analysis which can take into account the effect of a third variable on the correlation between two other variables. To apply this method to our experiment, first the Spearman correlation coefficient within subject between the incongruency score of softness (*Incongruency score*) and β values during application period (β_A) for the six lipsticks was calculated as $\rho_{Incongruency\ score.\beta_A}$. That between WTP scores and β values during the application period for the six lipsticks was given as $\rho_{WTP.\beta_A}$. That between the WTP scores and the incongruency scores was given as $\rho_{WTP.Incongruency\ score}$. From these three Spearman correlation coefficients, the semi-partial correlation between the incongruency scores and beta values during the application period controlling the effects of WTP values, $\rho_{Incongruency\ score.\beta_A|WTP}$, was calculated as below (Equation 3).

$$\rho_{Incongruency\ score.\beta_A|WTP} = \frac{\rho_{Incongruency\ score.\beta_A} - \rho_{WTP.\beta_A} * \rho_{WTP.Incongruency\ score}}{\sqrt{1 - \rho^2{}_{WTP.Incongruency\ score}}} \quad (\mathbf{3})$$

Intra-personal correlation analyses were performed as in our previous studies (Kawabata Duncan et al., 2019; Hirabayashi et al., 2021), therefore once the $\rho_{Incongruency\ score.\beta_A|WTP}$ was calculated for each subject, the value of each channel was converted into a Z score using Fisher's *r*-to-*z* transformation. Prior to conducting statistical analysis, it was essential to consider a reasonable effect size for the dataset of 27 participants. A power analysis was performed using G*Power 3.1.9.7 (Faul et al., 2007), with the following parameters: a sample size of 27, a one sample *t*-test for each channel, a type-I threshold (α) of 0.05, and power (1- β) of >0.8. This analysis yielded an effect size (Cohen's *d*) of 0.56, which was deemed reasonable (medium > 0.5) (Cohen, 2013). Subsequently, a one sample *t*-test was conducted to determine whether the average Z scores differed from 0. Following this, Fisher's *z*-to-*r* inverse transformation was applied to convert the average Z of all participants to the average coefficients of all participants.

4.3. Results

4.3.1. Behavioral Performance: Incongruency scores for softness

The incongruency scores for the six lipsticks are shown in **Figure 4.3-1**. During the test, participants rated their perception of the softness of the lipsticks from too hard (-50) to too soft (50) using a VAS. The values were converted into an incongruency score by taking the absolute value to visualize the distance of each VAS rating from 0, to ultimately produce the optimal softness score. In other words, if participants felt that the lipstick was of optimal softness, their incongruency score would be closer to 0. These incongruency scores were analyzed with a one-way repeated-measures ANOVA with lipstick samples as within-subject factors using JASP (Version 0.17.1). This revealed a significant main effect of lipstick ([$F_{(5, 145)} = 29.4$, $p < .001$, $\eta^2 = 0.50$], also see **Table 4.3-1**), suggesting that participants were able to discern differences in softness among the six different lipsticks. The incongruency scores, which represent deviation from the optimal softness score of 0, varied significantly across the lipstick samples. A lower incongruency score indicates that participants perceived the lipstick to be closer to the optimal softness.

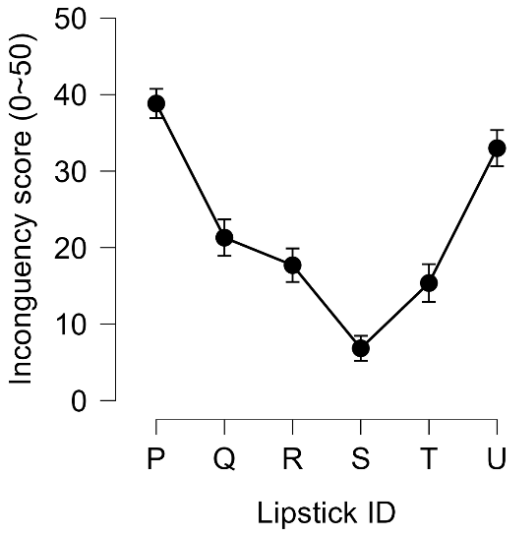

Figure 4.3-1 Average absolute values of incongruency scores (0~50) for six lipsticks

The graph shows the group average incongruency scores calculated by taking the absolute values of the perceived softness scores. P, Q, R, S, T, and U represent the six different lipsticks on a softness texture scale (soft to hard). Error bars represent the standard error of the mean.

4.3.2. Behavioral Performance: WTP

In addition to the perceived softness scores, participants were asked to rate their WTP for each lipstick. The average WTPs for the six lipsticks varied significantly, as shown in **Figure 4.3-2**. These data were analyzed using a one-way repeated measures ANOVA with lipstick samples as within-subject factors. This revealed a significant main effect of lipstick ([$F_{(5, 145)} = 9.57$, $p < .001$, $\eta^2 = 0.25$], also see **Table 4.3-1**), thus suggesting that the perceived softness significantly influences the overall evaluation of a lipstick. In other words, the greater the incongruency, the lower the participant's willingness to pay.

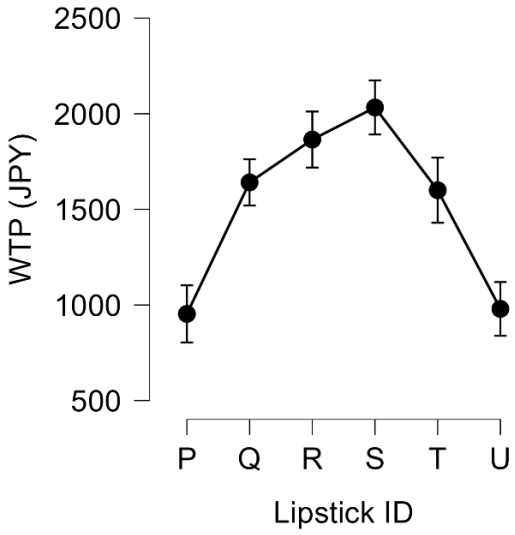

Figure 4.3-2 Average WTP (willingness-to-pay) for six lipsticks

The graph shows the group average WTP scores for six different lipsticks in Japanese yen (JPY). Error bars represent the standard error of the mean.

Table 4.3-1 Summary of the behavioral performance results

Lipstick ID	N	WTP score (JPY)		Incongruency score	
		Mean	SEM	Mean	SEM
P	30	953.3	181.7	38.8	2.2
Q	30	1641.0	213.8	21.3	2.5
R	30	1865.0	202.2	17.7	2.3
S	30	2032.7	202.5	6.8	1.4
T	30	1600.0	166.5	15.4	2.4
U	30	979.7	154.0	33.0	2.6

Note: Mean WTP and incongruency scores for all six lipsticks (n=30). SEM: Standard Error of the Mean

4.3.3. Intra-Personal Correlation

We investigated whether the brain activation in any specific brain area reflected the softness incongruency of the lipsticks. We first examined the correlation coefficients of all channels of all subjects, then computed the value of $\rho_{incongruency\ score.\beta_{Apply}|WTP}$ and converted these coefficients into Z values. The results of the mean *Z* in the group significantly differed from 0 in multiple channels (**Table 4.3-2)**. The results of 52 channels are described in **Figure 4.3-3,** and detailed numerical values can be found in the supplementary data. The one-sample *t*-test results for this channel were significant ([$t_{(26)}$ = 3.15, p<0.01, d = 0.61], also see **Appendix B**) based on the power analysis, only channel 8 showed an effect size *(d)* exceeding the reasonable threshold of 0.56. This was derived from a mean Z score of 0.31 and a standard error of the mean was 0.51. Figure 4 shows the observed hemodynamic response and the predicted response, which was created by combining regressors adjusted for each participant with the personalized adaptive GLM. Ch 8 covered the right IFG, based on the results of the MNI coordinates (x=58.0, y=36.3, z=0.7, SD=8.3), with microanatomical estimation of the right IFG via LBPA40 (Shattuck et al., 2008). After *z* to *r* conversion, the group average of mean $\rho_{Incongruency\ score.\beta_{Apply}|softness}$ was 0.30 at Ch 8.

Table 4.3-2 Channels of mean Z in the group significantly differed from 0

Channel	Mean R	Mean Z	SD	*t*	*p*	*d*	1-*β*	*df*
4	0.29	0.30	0.70	2.19	0.04	0.42	0.56	26
7	0.23	0.24	0.50	2.46	0.02	0.47	0.66	26
8	0.30	0.31	0.51	3.15	0.004	0.61	0.86	26
11	0.23	0.24	0.52	2.36	0.03	0.45	0.62	26
14	0.30	0.31	0.71	2.27	0.03	0.44	0.59	26
18	0.32	0.33	0.59	2.88	0.01	0.55	0.79	26
19	0.27	0.28	0.65	2.18	0.04	0.43	0.55	25
21	0.20	0.20	0.40	2.54	0.02	0.5	0.69	25
39	0.19	0.19	0.47	2.12	0.04	0.41	0.53	26

Channels for which the mean Z-score, derived from $\rho_{Incongruency\ score.\beta_{Apply}|WTP}$, was significantly different from 0 in the one-sample *t*-test. SD: standard deviation; *t*: *t*-value; *d*: Cohen's *d; p*: *p*-value; *1-β*: power, *n*=27. Additionally, the Mean R, calculated from the Mean Z using the inverse Fisher's *z*-to-*r* transformation, is also provided.

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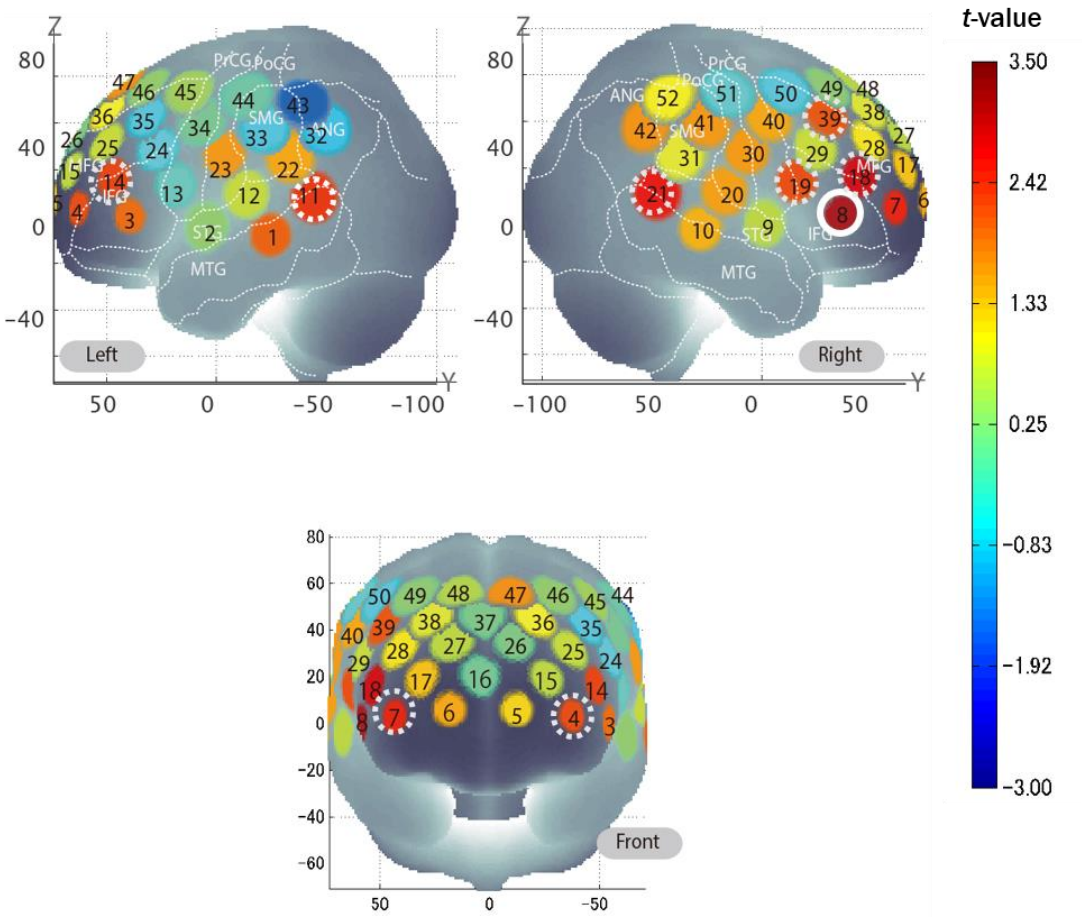

Figure 4.3-3 Group average of semi-partial correlation coefficients across 52 channels for incongruency score

Based on the *t*-values resulting from one-sample *t*-tests for the mean Z of $\rho_{Incongruency\ score.\beta_A|softness}$ for each channel, the corresponding values were plotted according to the color-bar. Ch 8, covering the right IFG, is encircled by a solid white line as it was found to be significantly different from 0 and demonstrated a sufficient effect size. Additionally, channels that were found to be statistically significant (Ch 4, 7, 11, 14, 18, 19, 21, and 39) are encircled by a dotted white line.

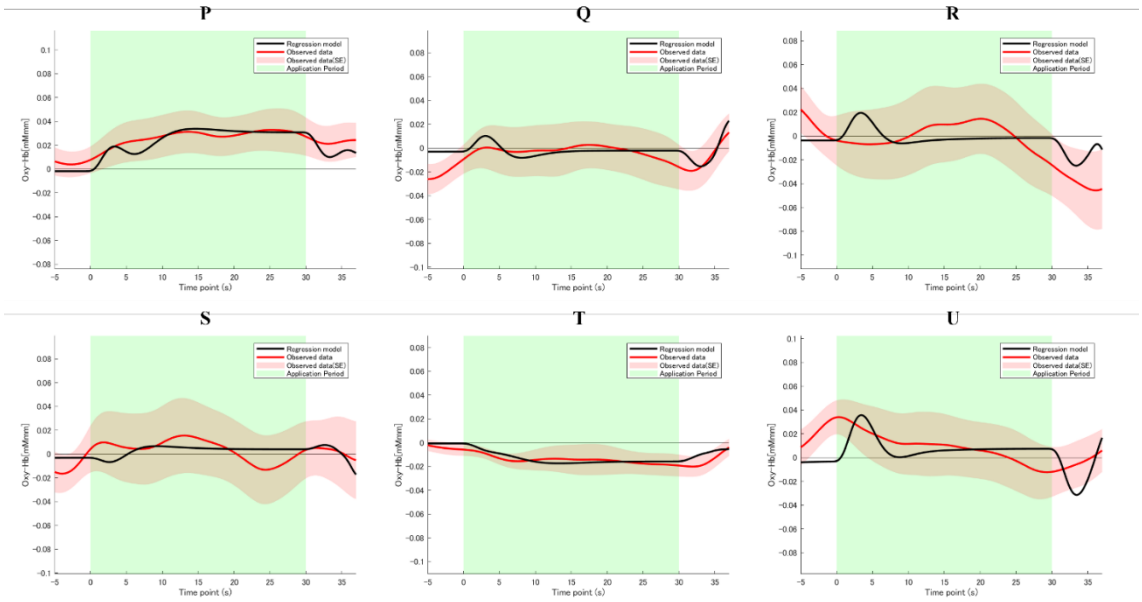

Figure 4.3-4 fNIRS time series data for Ch 8 during lipstick application

The graphs show the observed and predicted time-series data for fNIRS from all channels for six lipstick samples (P, Q, R, S, T, and U), averaged across all subjects, n=27. The red lines indicate the observed oxygenated hemoglobin (oxy-Hb) signal, and the black lines indicate predicted hemodynamic responses. Standard errors are shown as pale red (n=27). The green highlighted area is the 30 s of the application period.

4.4. Discussion

The aim of the present study was to investigate the feasibility of a real-time brain-based product evaluation method which detects the incongruency between a product and a consumer's expectations. We looked for brain areas where activation was related to the incongruency of the softness of lipsticks. We found significant intra-subject correlations between the incongruency score and activation in the right IFG. These correlations were revealed using semi-partial correlation analysis, which allowed us to control the influence of the third variable of WTP. This is the first step towards a commercially applicable brain-based measurement which can help reveal specific features of a product, such as the softness of a lipstick, which are failing to meet consumer expectations and, therefore, assist in product development.

Importantly, the current study builds upon our prior research by confirming intra-subject correlations multiple times (Kawabata Duncan et al., 2019; Hirabayashi et al., 2021). By focusing on the incongruity of a cosmetic item's texture with participants' expectations, we have expanded our understanding of the relationship between the monetary evaluation

of cosmetic products and the cortical activation concurrently evoked. Unlike previous studies that solely relied on WTP values to assess overall scores of cosmetics, our investigation specifically examined how texture features influence WTP scores. These findings offer valuable insights that can inform product formulation and optimize texture. Furthermore, our results feature the significance of individual variations in brain activity, emphasizing the necessity of intra-subject analyses to capture meaningful associations.

Moreover, applying schema congruency theory to lipsticks leads to the prediction that the more the softness of a lipstick deviates from a consumer's optimal preference, the worse the consumer evaluation will be (Meyers-Levy & Tybout, 1989; Huang et al., 2013). Consistent with this, we found an inverse correlation between softness incongruency and WTP, which also confirms the critical role of softness in the experience of lipstick. Crucially, we observed an intra-subject correlation between the incongruency score of the lipsticks and activation in the right IFG. We suggest that the greater activation in the right IFG can be interpreted as the brain's response to the incongruency between a product and a consumer's expectations. This is consistent with previous studies such as that of Sherman and colleagues (2016), who found that the right IFG is sensitive to the discrepancy between expectation and decision and that of Allen and colleagues (2016), who observed tactile mismatch responses in the right IFG using fMRI.

In addition to the activation of the right IFG, we observed that several other cortical regions were associated with the incongruency score. This might be attributable to the involvement of working memory. In our study, participants engaged in the evaluation of the physical properties of a lipstick and this is in line with the concept of exploratory decision-making (Daw et al., 2006; Krug et al., 2014; Domenech & Koechlin, 2015). Once the lipstick incongruity score is formed individually, the respective WTP values should be determined. Previously, neuroimaging of working memory during sensory evaluation was performed with fNIRS. Okamoto and colleagues (2011) found that the right hemispheric lateral PFC, including the DLPFC and extending to parts of the ventrolateral prefrontal cortex (VLPFC) such as the IFG, was activated during memory retrieval. Considering these findings, we postulated that the prefrontal cortices are important for integrating multiple sensory cues including tactile and taste information. Thus, our study provides a crucial key to understanding cognitive processes that occur during tactile sensory evaluations, which constitutes an important step in the development and formulation of cosmetic products.

Due to the limitations of fNIRS, specifically that it is unable to detect signals from structures that do not lie directly below the scalp, we are not able to measure activation in areas, such as the ACC, which have been associated with the processing of incongruity (Noseworthy et al., 2014; Kolling et al., 2016; Clairis & Lopez-Persem, 2023). Therefore, it may be the case that such areas would provide more robust biomarkers for incongruency during product experience. However, measuring these areas with fMRI is at odds with the main objective of this research, which is to measure consumers' real-time experience of cosmetics in as natural a setting as possible; the application of cosmetics in an fMRI scanner is very difficult.

5. General discussion

5.1. General Conclusions

The purpose of this dissertation is to establish the viability of fNIRS as a product evaluation method by validating and exploring prefrontal activation based on the correlation with subjective product evaluation scores.

Study 1 highlighted the potential of fNIRS to provide brain-based insights into consumer behavior and decision-making in the context of cosmetics products. The results revealed a significant positive correlation between the degree of activation in the right DLPFC during lipsticks use and their respective WTP values, consistent with the previous study. The findings suggest that the activation in the right DLPFC during the use of cosmetics may serve as a potential biomarker for personalization or product selection processes. However, the study did not find consistent group differences in the degree of activation in the right DLPFC between different lipstick colors and textures, despite manipulating these variables to maximize differences. Additionally, there were no consistent differences in WTP values among the different lipsticks. The findings suggest that the activation of the right DLPFC during the use of cosmetics may serve as a potential brain-based biomarker for personalization or product selection process but is not necessarily a suitable biomarker for all consumer preferences.

Furthermore, Study 2 aimed to explore the use of fNIRS to provide additional information about consumers' experiences with cosmetics and develop a brain-based measurement of consumer experience. The results of the study demonstrated a significant intra-subject correlation between incongruency scores of softness and brain activation in the right inferior frontal gyrus (IFG), indicating that the right IFG may play a role in detecting incongruity between perceived texture and consumer expectations.

The analysis method using intra-subject correlations explored the relationship between overall monetary evaluation for a product associated with activation in the right DLPFC. This previous finding was successfully replicated in Study 1 and the right IFG was negatively correlated with the incongruency score of lipsticks which was a new finding in Study 2. These results highlighted the potential significance of both the right DLPFC in overall cosmetics evaluation and the right IFG in discerning incongruencies related to cosmetics texture. This suggests that these neural regions could serve as potential biomarkers for the evaluation of cosmetics, paving the way for personalized approaches

and a deeper understanding of the product selection processes. Ultimately, this research holds the promise of facilitating the creation of more appealing and successful cosmetic products in the market.

5.2. Limitations and Recommendations for Future Research

Specifically, the experiments conducted in real-time and single-time experiences within ecologically valid settings, where participant movement is flexible, emphasized the practical applications of using fNIRS in the evaluation of cosmetic products. These findings emphasize the potential for fNIRS to offer a deep understanding of consumer responses in real-world scenarios, contributing to the practical utility of this neuroimaging technique in the field of cosmetics research.

Additionally, our studies explored the neural mechanisms underlying the product evaluation process. Initially, we manipulated the lipstick color based on individual preferences and evaluated products with varying textures using WTP to quantify consumer evaluation. We then refined our approach to exclusively focus on lipstick textures. In this phase, lipstick samples were evaluated with WTP based on perceived texture. This methodology was further refined to concentrate on texture alone, allowing us to explore how texture, independently of color preference, influences overall evaluation. These studies offered a deeper understanding of the neural mechanisms behind texture perception incongruence. This stepwise refinement highlights the impact of texture for the product evaluation and understanding the process of detecting incongruence at the neural level.

The studies highlighted the capability of incorporating neuroscientific measures into product testing to predict consumer reactions, emphasizing the need to understand the underlying reasons for the correlation between brain activity and consumer behavior before commercial implementation.

In terms of limitations, Study 1 did not find consistent group differences in the activation of the right DLPFC between different lipstick colors and textures, despite manipulating these variables to maximize differences. Additionally, there were no consistent differences in WTP values among the different lipsticks. Study 2 only focused on the results of semi-partial correlations between brain activation during lipstick use and the incongruency score. These suggested that predicting or determining group-level differences based on these specific factors such as lipstick colors or softness is still

challenging.

This may have been because of the limitation on the number of trials possible with cosmetics in a single test due to ethical reasons about the participants' burden. Specifically, it is difficult to repeat many times to try samples in the experiment. One potential strategy to overcome the limitation is accumulating more data over time. This approach allows for understanding of consumer behavior and preferences by analyzing and forecasting how different factors, such as texture, influence their purchasing decisions.

Applying machine learning to neuroscience, in general, is becoming a trend in this decade, for instance, this approach has proven useful for identifying complex patterns related to psychiatric disorders, understanding decision-making processes, and assisting in disease classification, predicting treatment outcomes, and enhancing treatment selection (Plis et al., 2014; Huys et al., 2016; Vieira et al., 2017). This trend highlights machine learning's capability to analyze and interpret brain data, providing insights beyond traditional analysis methods.

By analyzing the detailed patterns in each person's brain data, machine learning offers a new way to explore the complex process of the human mind, showing us not just what happens in specific parts of the brain, but also how all the parts work together over time. This method has recently found its way into consumer neuroscience as well.

The application of machine learning in neuroscience extends beyond merely identifying significantly activated brain areas. It involves analyzing the entirety of brain activations, treating them as parameters within complex models to understand and predict consumer behavior more accurately (Lemm et al., 2011). This comprehensive approach allows researchers to capture subtle differences in consumer responses that traditional methods might overlook.

Applying machine learning to neuroscience, in general, is becoming a trend in this decade, for instance, machine learning techniques have been applied for diagnostic classification within clinical studies, demonstrating the potential of brain data to uncover hidden patterns (Huys et al., 2016).

Furthermore, machine learning has been increasingly applied in marketing research, such as in assessing the impact of advertisements (Hakim et al., 2023; Wei et al., 2018) and

WTP prediction (Telpaz et al., 2015), specifically using EEG data. Recently, some studies applied fNIRS to predict consumer preferences (Qing et al., 2021), classifying subject-level responses based on fNIRS signals (Hiwa et al., 2016). Çakir and colleagues have highlighted the potential application of machine learning to fNIRS data as a potential method for predicting consumer purchase decision to worth exploring (Çakir et al., 2018) and currently, they are trying to predict consumers' financial decisions during measurement with fNIRS (Çakar et al., 2023). This suggests that there is a future potential to predict subject-level preferences or evaluation to understand consumer behaviors from brain activations related to the marketing stimuli.

Another promising approach to address the limitations of cosmetic trials is the use of multi-neurophysiological methods, which present a viable alternative for gathering rich data even with a limited number of trials. A study of Venkatraman and colleagues (2015), examined the application of multi-neurophysiological methods, such as fMRI, biometrics, and EEG, to predict advertising effectiveness beyond traditional measures of self-report. This was a multi-method protocol using the same stimuli allowing a comparison across traditional and neurophysiological methods. The study found that only fMRI activity in the ventral striatum (VS) explains more variance in advertising elasticities than traditional measures which is similar to the previous study (Berns & Moore, 2012) which predicted the group levels of the future music sales correlated with the VS activations.

These results tell us that the multi-neurophysiological methods highlight the profound importance of brain data, which includes more than just the explicit responses gathered through subjective ratings. By analyzing brain responses, particularly in regions like the VS, we can gain a direct insight into the underlying processes that influence consumer decisions, revealing a product's impact and value that conventional methods cannot capture. The point of using neurophysiological methodologies is not only to identify the neural mechanisms underlying consumers' behaviors but also more comprehensive understanding of consumer behavior, bridging the gap between explicit data and the rich insights that lie within the brain's response to the marketplace.

5.3. Future Perspectives

Recent trends, the COVID-19 pandemic has heightened the focus on well-being across various industries, including the luxury cosmetics market. The perception of cosmetics has changed beyond only a solution for imperfections to expressing individual identity. This shift emphasizes the growing importance for brands to understand consumer insights

and create personalized experiences in order to enhance communication with their consumers in the competitive market. Thus, marketers are challenged not only to grasp the distinctive desires and preferences of their target audience but also to distinguish themselves in the market by delivering extraordinary and superior cosmetic experiences that evoke a sense of uniqueness for the consumers.

Additionally, objective evidence of luxury feelings serves as a meaningful strategy for both marketers and consumers, affirming the superior quality of the product. Even for abstract luxury feelings, an avenue to achieve this could be through the application of the schema congruity concept. According to the previous study, personality congruence with a brand is positively linked to brand attachment (Donvito et al., 2020). In other words, when an individual perceives a match between their own personality and the brand's personality, they are more likely to develop a strong emotional bond and attachment to the brand.

Analyzing brain activation during the cosmetics experience about abstract concept of luxury including cognitive dimensions like willingness-to-pay and emotional process of resonance (Ko et al., 2019) may be challenging to capture through brain imaging as its complexity and subjectivity of the concept.

A study conducted by He et al. (2021) sheds light on understanding abstract concepts with fNIRS. The results of the intra-subject correlation analysis showed that there were differences in neural activations when participants viewed low-scoring ads compared to high-scoring ads, particularly in the medial prefrontal cortex (mPFC) and the inferior frontal gyrus (IFG). The inter-subject correlation analysis, on the other hand, focused on the network density and synchronous patterns of activations across all participant brains while they experienced the same media content. The study found that the network density in the right IFG positively predicted participants' attitudes and emotional responses to the content, indicating a potential shared resonance and understanding among the participants.

Building upon the findings of He et al. (2021), our studies has similarly identified the intra-subject correlations which identified differences in neural activations within the same participant when exposed to different stimuli. However, the emphasis on synchronous patterns of network activity, rather than the sole consideration of activation levels, can present a promising way for the future investigations.

By acknowledging that individuals exhibit shared resonance and understanding during exposure to specific media content, personalized advertising strategies is one of the insights. Understanding the synchronized neural responses within and across individuals may serve as a foundational element for tailoring advertisements to align with the cognitive and emotional preferences of targeted audiences. Not only the ads, as our studies tried to explore the interaction between consumers and products, this neural synchrony can be involved into product development based on real-time assessments by consumers.

The investigation into synchronous patterns of neural network activity holds promise not only in the realm of personalized advertising and product creation but also in unraveling the complexities of abstract concepts. As highlighted by Tanida et al. (2017), employing neuroscientific tools to visualize the feelings of pleasantness during cosmetic experiences has become crucial. Moreover, as technology advances and our understanding of neural processes deepens, the potential for personalized product creation becomes increasingly feasible, guiding us into to a new era of consumer-centric design and manufacturing.

Regarding interpersonal synchronization, a prominent trend in the current era involves the practice of hyper-scanning. Pinti and colleagues (2018) posit that exploring social neuroscience using fNIRS offers various advantages, such as its capability of real-time assessment, flexibility, and the ability to operate in naturalistic settings. This technology proves invaluable for delving into the complexities of social interactions, providing a dynamic and adaptable approach to investigating the neural underpinnings of interpersonal synchronization. By employing hyperscanning, allows for the investigation of how individuals collectively engage with and respond to products in a social context, offering unique perspectives on consumer behavior and group dynamics.

Therefore, the interaction between consumers and products can be explored in the context of inter-personal aspects to study during interactions with products. Based on the advantages of using fNIRS, future applications in a retail environment could lead to an enhanced shopping experience through tailored product offerings and marketing strategies that align with consumer preferences and expectations.

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My appreciation also goes out to my parents, family, my dog who beside me while I do a lot of work, colleagues, and friends for their sincere support, encouragement and understanding all through my studies.

Appendix A

Table A1: Results of one sample *t*-test of 52 channels

Channel	*t*	*p*	*d*	MeanR
1	0.74	0.47	0.15	0.07
2	-0.84	0.41	-0.17	-0.06
3	1.82	0.08	0.36	0.18
4	0.81	0.42	0.16	0.11
5	-0.50	0.62	-0.10	-0.06
6	-0.54	0.59	-0.11	-0.07
7	-0.63	0.53	-0.13	-0.07
8	-0.59	0.56	-0.12	-0.06
9	0.57	0.58	0.11	0.08
10	0.19	0.85	0.04	0.02
11	1.38	0.18	0.28	0.13
12	-2.04	0.05	-0.41	-0.14
13	0.35	0.73	0.07	0.05
14	0.80	0.43	0.16	0.10
15	0.56	0.58	0.11	0.08
16	0.16	0.87	0.03	0.02
17	-1.13	0.27	-0.23	-0.16
18	-0.35	0.73	-0.07	-0.03
19	-0.26	0.80	-0.05	-0.03

20	0.56	0.58	0.11	0.07
21	-0.45	0.66	-0.09	-0.05
22	-0.85	0.40	-0.17	-0.10
23	-0.06	0.96	-0.01	-0.01
24	-0.07	0.94	-0.01	-0.01
25	1.13	0.27	0.23	0.11
26	0.86	0.40	0.17	0.06
27	NaN	NaN	NaN	NaN
28	1.31	0.20	0.26	0.14
29	-1.08	0.29	-0.22	-0.11
30	0.79	0.44	0.16	0.10
31	0.74	0.47	0.15	0.08
32	0.62	0.54	0.12	0.07
33	0.26	0.80	0.05	0.02
34	-0.15	0.88	-0.03	-0.02
35	1.98	0.06	0.40	0.19
36	0.93	0.36	0.19	0.10
37	0.53	0.60	0.11	0.06
38	**2.62**	**0.02**	**0.52**	**0.23**
39	0.46	0.65	0.09	0.04
40	-0.48	0.64	-0.10	-0.04

41	0.27	0.79	0.05	0.03
42	0.30	0.77	0.06	0.04
43	-0.49	0.63	-0.10	-0.05
44	0.89	0.38	0.18	0.10
45	1.27	0.22	0.25	0.14
46	0.13	0.89	0.03	0.02
47	0.17	0.87	0.03	0.02
48	1.71	0.10	0.34	0.21
49	1.43	0.17	0.29	0.13
50	0.86	0.40	0.17	0.08
51	1.44	0.16	0.29	0.22
52	0.56	0.58	0.11	0.06

Appendix B

Table B1: Results of one sample *t*-test of mean Z obtained from $\rho_{Incongruency\ score.\beta_{Apply}|WTP}$ and Mean R for each channel

Channel	Mean R	Mean Z	SD	*d*	*t*	*p*	1-*β*	*df*
1	0.19	0.19	0.48	0.40	2.05	0.051	0.50	25
2	0.02	0.02	0.40	0.06	0.30	0.770	0.06	25
3	0.16	0.16	0.42	0.38	1.98	0.058	0.48	26
4	**0.29**	**0.30**	**0.70**	**0.42**	**2.19**	**0.038**	0.56	26
5	0.13	0.14	0.54	0.25	1.30	0.206	0.24	26
6	0.21	0.21	0.68	0.31	1.59	0.123	0.34	26
7	**0.23**	**0.24**	**0.50**	**0.47**	**2.46**	**0.021**	0.66	26
8	**0.30**	**0.31**	**0.51**	**0.61**	**3.15**	**0.004**	0.86	26
9	0.08	0.08	0.60	0.13	0.69	0.499	0.10	26
10	0.21	0.21	0.69	0.30	1.52	0.143	0.31	24
11	**0.23**	**0.24**	**0.52**	**0.45**	**2.36**	**0.026**	0.62	26
12	0.07	0.07	0.47	0.15	0.77	0.449	0.11	26
13	-0.04	-0.04	0.51	-0.07	-0.36	0.719	0.06	26
14	**0.30**	**0.31**	**0.71**	**0.44**	**2.27**	**0.032**	0.59	26
15	0.07	0.07	0.51	0.14	0.72	0.477	0.11	26
16	-0.01	-0.01	0.64	-0.01	-0.04	0.965	0.05	26
17	0.14	0.15	0.54	0.27	1.41	0.170	0.27	26
18	**0.32**	**0.33**	**0.59**	**0.55**	**2.88**	**0.008**	0.79	26
19	**0.27**	**0.28**	**0.65**	**0.43**	**2.18**	**0.039**	0.55	25
20	0.16	0.16	0.51	0.31	1.64	0.114	0.35	26
21	**0.20**	**0.20**	**0.40**	**0.50**	**2.54**	**0.018**	0.69	25
22	0.15	0.16	0.51	0.30	1.58	0.127	0.33	26
23	0.19	0.19	0.58	0.32	1.69	0.104	0.37	26
24	-0.05	-0.05	0.44	-0.11	-0.59	0.560	0.09	26
25	0.07	0.07	0.47	0.15	0.79	0.438	0.12	26
26	0.01	0.01	0.73	0.02	0.09	0.930	0.05	26
27	0.08	0.08	0.59	0.13	0.69	0.494	0.10	26
28	0.13	0.13	0.57	0.23	1.19	0.246	0.21	26
29	0.08	0.08	0.54	0.16	0.80	0.430	0.12	25
30	0.17	0.17	0.52	0.33	1.67	0.107	0.36	25

31	0.10	0.10	0.54	0.19	0.99	0.330	0.16	25
32	-0.08	-0.09	0.52	-0.16	-0.83	0.413	0.13	25
33	-0.09	-0.09	0.61	-0.14	-0.73	0.471	0.11	26
34	0.00	0.00	0.48	0.00	-0.02	0.985	0.05	26
35	-0.08	-0.08	0.57	-0.13	-0.69	0.497	0.10	26
36	0.10	0.10	0.48	0.21	1.10	0.281	0.19	26
37	0.01	0.01	0.62	0.01	0.06	0.955	0.05	26
38	0.08	0.08	0.46	0.18	0.96	0.347	0.15	26
39	0.19	0.19	0.47	0.41	2.12	0.044	0.53	26
40	0.14	0.14	0.44	0.31	1.58	0.126	0.33	25
41	0.21	0.22	0.67	0.32	1.68	0.105	0.37	26
42	0.25	0.25	0.76	0.33	1.72	0.098	0.38	26
43	-0.19	-0.19	0.65	-0.29	-1.52	0.141	0.31	26
44	-0.02	-0.02	0.48	-0.03	-0.17	0.864	0.05	25
45	0.05	0.05	0.57	0.09	0.46	0.652	0.07	26
46	0.03	0.03	0.56	0.06	0.32	0.753	0.06	25
47	0.16	0.16	0.48	0.33	1.74	0.094	0.39	26
48	0.06	0.06	0.53	0.12	0.61	0.549	0.09	25
49	0.03	0.03	0.60	0.05	0.25	0.806	0.06	23
50	-0.07	-0.07	0.50	-0.13	-0.66	0.518	0.10	24
51	-0.04	-0.04	0.45	-0.09	-0.49	0.626	0.08	26
52	0.12	0.12	0.54	0.22	1.13	0.269	0.19	26

Table showing the results from the one-sample *t*-test differed from 0 for the mean *Z* derived from $\rho_{Incongruency\ score.\beta_{Apply}|WTP}$ for 52 channels with the following values: *t* = *t*-values; SD=standard deviations; *d* = Cohen's *d; p* = *p*-values; *1-β* = power, n=27. Values with $p<0.05$ are highlighted in bold and as channel 8 only has power $1-\beta>0.8$, those are in red. Additionally, the Mean R, calculated from the Mean Z using the inverse Fisher's *z*-to-*r* transformation, is also provided (Mean R).

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