Learning and Representation of Planning Ability in the Human Brain: Executive Function and Decision Making

by

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Abstract

In this dissertation, I describe the three investigated results that brain representations are involved with decision-making. Firstly, we examined a transition of brain activation in decision-making at problem-solving by long-term learning. The methodology of this study involves the Tower of Hanoi (ToH) to investigate executive functions related to the learning process. Generally, ToH is used to measure baseline performance, learning rate, offline learning, and transfer. However, this study performs experiments on long-time learning effects for ToH solving. The participants were involved in learning the task over seven weeks. Learning progress was evaluated based on improvement in performance and correlations with the learning curve. All participants showed a significant improvement in planning and decision-making over seven weeks of time duration. Brain activation results from functional magnetic resonance imaging (fMRI) showed a statistically significant decrease in the activation degree in the dorsolateral prefrontal cortex, parietal lobe, inferior frontal gyrus, and premotor cortex between before and after learning. Our pilot study showed that updating information and shifting issue rules were found in the frontal lobe. Through monitoring performance, we can describe the effect of long-time learning initiated at the frontal lobe and then convert it to a task execution function by analyzing the frontal lobe maps. This process can be observed by comparing the learning curve and the fMRI maps. It was also clear that the degree of activation tends to decrease with the number of tasks, such as through the mid-phase and the end-phase of training. The elucidation of this structure is closely related to decision-making in human behavior, where brain dynamics differ between "thinking and behavior" during complex thinking in the early stages of training and instantaneous "thinking and behavior" after sufficient training. Since this is related to human learning, elucidating these mechanisms will allow the construction of a brain function map model that can be used universally for all training tasks. Next,

we focused on brain activation during the decision-making process, which was selected based on a single evaluation criterion. Neuro-marketing, which explores the human decision-making process, is attracting attention by measuring the reaction of the brain in an objective way, and taking advantage of progress in brain science and psychophysics. Numerous studies have been conducted to date on preference-based decision-making, and the evaluation criteria of the decision-making process are diverse, such as food preferences, product costs, or facial features. In this research, decision-making experiments by several evaluation criteria were conducted using fMRI scanner in order to elucidate the brain regions comprehensively involved in decision-making and specific brain regions related to each evaluation criterion. This experiment measured brain activity during paired comparison tasks based on a single evaluation criterion by fMRI, and attempted to identify specific brain regions related to decision-making based on each evaluation criterion. Participants performed a decision-making task that involved choosing a smartphone by referring to information such as price, color or year as an evaluation criterion. As a common activation region in the choice tasks by all evaluation criteria, the bilateral occipital gyri had significant activation. The result is consistent with reports of previous studies which indicate that the occipital gyrus is the brain region related to visual processing and preference-rated tasks. Conversely, with specific activation regions involving color choice tasks, the left fusiform gyrus, left insula and right precuneus are significantly activated. The result suggests that attention to color choice becomes greater than other choices. Finally, we investigated the representation of evaluation criterion categories in decision-making using the multi-voxel pattern analysis (MVPA) method. Several studies using traditional analysis have attempted to explain the neural mechanisms associated with decision-making based on abstract rewards. However, brain-decoding research that utilizes the MVPA, especially research focusing on decision-making, remains limited. In brain analysis, decoding

strategies for multivoxels are required for various decision-making evaluation criteria. This is because, in daily life, the human decision-making process makes use of many evaluation criteria. In the present study, we investigated the representation of evaluation criterion categories in decision-making using functional magnetic resonance imaging and MVPA. Participants performed a decision-making task that involved choosing a smartphone by referring to four types of evaluation criteria. The regions of interest (ROIs) were the ventromedial prefrontal cortex (vmPFC), nucleus accumbens (NAcc), and insula. Each combination of the four evaluation criteria was analyzed based on a binary classification using MVPA. From the binary classification accuracy obtained from MVPA, the regions that reflected differences in the evaluation criteria among the ROIs were evaluated. The results of the binary classification in the vmPFC and NAcc indicated that these regions can express evaluation criteria in decision-making processes.

Acknowledgements

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Chapter 1

Introduction

1.1 Motivation and Overview

In human life, people make decisions hundreds to thousands of times a day. Life involves many decisions, ranging from mundane to critical. These decisions are based on life experiences and values and lead to personal growth and goal achievement. People make decisions all the time throughout their lives, and these decisions shape their experiences and help them achieve their goals. These decisions range from simple day-to-day choices to more important long-term decisions that greatly impact a person's life. Factors such as values, past experiences, and personal goals all shape the decisions people make.

This dissertation focuses on two things related to decision-making. One is a transition of brain Activation in decision-making at problem-solving by long-term learning. We focus on learning executive functions, which include decision-making, cognitive processing, and planning. Regarding learning, memories and expressions are established by biological feedback, such as visual perception and haptics. This feedback affects the learning processing time and efficiency. The executive function consists of the same lower-level functions, such as divided attention, processing ability for multiple tasks, conversion ability of a thought set, thinking speed,

and inductive guessing [1]. Impaired executive function significantly influences individual ability, planning, prioritization, organization, attention and detailed memory, emotional response control, and planning and decision-making [2], is considered to include the frontal lobe. Executive function and planning require foresight and empirical knowledge. Planning and decision-making become logical choices from available options. In other words, this can explain the evaluation and selection of several conflicting alternatives. When making a good choice, it is necessary to measure the advantages and disadvantages of all considerations. For effective planning and decision-making, predicting each option's outcome from a task operation are essential. The best item from all options depends on the outcome predicted for the situation. Therefore, all planning and decision-making result from a definitive choice [3]. From a recognition perspective, interactions in a task environment are integrated into ongoing procedures/proceedings and are significant in the planning and decision-making process. The planning and decision-making results are related to an unchangeable selection based on logic and rationality.

The other focus point is brain representation by human choice in purchase decision-making. We focus on evaluation criteria, which is the motivation for choosing decision-making. The field of neuro-marketing, which explores the human decision-making process by objectively measuring brain reactions and taking advantage of brain science and psychophysics knowledge, is attracting increasing attention [4, 5]. The neuroscience field uses fMRI, functional near-infrared spectroscopy, positron emission tomography, and electroencephalography to explore human decision-making processes[6, 7]. Several studies using traditional univariate analysis have attempted to elucidate the neural mechanisms associated with decision-making based on abstract rewards.

Multi-voxel pattern analysis (MVPA) has been attracting increasing attention, as shown in recent fMRI studies to elucidate brain activity patterns [8–10]. A relatively

large amount of the existing research using MVPA focuses on decision-making because it is important to understand which brain regions are involved in the various metrics used during decision-making in daily life. Given this background, the present study aimed to estimate user choice in decision-making based on brain activity.

1.2 Structure of the Dissertation

This dissertation consists of four chapters. The content of the dissertation is as follows.

- Chapter 1 introduces the motivation and overview of this research.
- Chapter 2 focuses on brain activity before and after learning. The effect of the planning and decision-making process concerning executive function on brain activity via long-time learning was investigated.
- Chapter 3 focuses on brain activation during the decision-making process, which was selected based on a single evaluation criterion. The fMRI result showed brain regions with common brain activation and specific brain activation during the selection task. Moreover, MVPA results showed that some brain regions could express the influence of the evaluation criteria during decision-making.
- Chapter 4 concludes this dissertation.

Chapter 2

A Transition of Brain Activation in Problem-Solving by Long-Term Learning

2.1 Introduction

Identifying the areas of significant activation in the brain and their relation to executive function, including cognition, as a particular brain mechanism [11], is essential to clarify the effects to investigate the impact of planning and decision-making processes in long-time learning. Executive function is defined as a goal–direction behaviour, including planning for the short-term future. The ability to maintain an appropriate attitude for achieving future goals relies on four main points, according to Lezak et al., such as goal formulation, planning, carrying out goal-directed plans, and effective performance [1]. Executive function involves higher-order information from any sensory stimulus. Higher-order executive function processes transmit information to the brain. The prefrontal cortex (PFC) is closely involved in executive function and plays crucial roles in planning, executive processing, and emotional expression. The ToH task measures planning abilities by systematically varying planning demands [12–14].

In the ToH task, a player must rearrange a set of multiple disks on three pegs

of varying sizes from the start state to the goal state using the minimum number of moves. Completing this task is known to be critically dependent on PFC activation [11, 15–22]. Therefore, the ToH task is considered appropriate for investigating the role of the PFC.

On the other hand, previous studies have confirmed activation of the dorsolateral PFC (DLPFC) during the ToH task. Some researchers have argued that the ToH task activates the DLPFC (BA 9), parietal lobe (BA 7, 40), inferior frontal gyrus (BA 44), and premotor cortex (BA 6) [23–27].

Card et al. studied the minimum reaction time when starting an exercise after a short-time judgment of human acquisition from visual information. The model human processor (MHP) is a famous model of human processing developed by Card [28]. Humans have a minimal response time of more than 370 ms (eye movement processor = 230 ms, cognitive processor = 70 ms, motor processor = 70 ms) from the time information is sent and the planning and decision behavior. Puzzle tasks in this experiment do not have any delay or prediction error between the screen information and behavior. By pressing a button, participants can predict the next state based on planning and decision-making.

Human decision-making is a complex process involving many factors. There may also be a stochastic element in it. However, human decision-making is generally regarded as a decisive process, and stochastic factors are often not considered. Also, Human decision-making is a complex process that involves many factors, such as cognitive biases, emotions, past experiences, and social influences. It may also involve a degree of randomness or stochasticity, as the individual may not have all the information needed to make a fully informed decision. However, it is generally viewed as a decisive process, and the role of stochastic factors may not be fully considered. It can be said that operators can make good decisions when they have enough information. In this case, having accurate and relevant information is necessary to make good decisions. In the ToH task, participants have the

whole information for a solution, there is no stochastic element. The operation depends on precise planning and decision, and participants can perform the task in less time. The time lags during these operations are caused mainly by the planning and decision-making process based on visual information. In some control cases for various planning and decision-making processes, the time lag is about 400–500 ms [28]. If learning levels are sufficiently advanced; participants can control these times. Trends in the time lags in button pressing correlate with trends in the temporal learning time. fMRI and outside training environments have the same time lag and learning properties.

The present study focuses on the brain regions mainly involved in executive function, including the DLPFC, parietal lobe, inferior frontal gyrus, and premotor cortex [23–27]. Our investigation is to observe changes in the degree of activation depending on the learning status of the learners.

This long-time learning experiment was conducted using a ToH puzzle, frequently used to measure learning ability [11, 29–32]. The long-time learning experiment consisted of a learning term and three MRI terms. In the learning term, learners studied the ToH puzzle outside the fMRI scanner for seven weeks. The three MRI terms were conducted at the end of the learning term's starting, middle, and final third.

2.2 The Tower of Hanoi

The ToH is a popular puzzle in cognitive psychology and neuropsychology used to assess a set of behaviors collectively referred to as executive function. In addition, the ToH is also a popular puzzle game for cognitive science and neuroscience [11, 29–32]. This task is typically used to evaluate behaviors and executive function. In the current experiment, estimating the brain activation recursively was attempted. Inductive inference is an estimation method that identifies general rules of individual, partial, and special events [33, 34]. The ToH puzzle is a complex cognitive task

in which participants must learn the procedural process for disk operation. The guidelines of this game can be explained as follows.

The detailed rules are as follows:

1. The ToH puzzle consists of three poles and different-sized disks.
2. In the initial position, all disks are stacked on the left pole in ascending order.
3. Participants can only move one disk at a time.
4. The disks can be moved from one pole to another.
5. The disks can be placed on an empty pole or larger disks.
6. A larger disk cannot be placed on top of a smaller disk.
7. The goal is to move all the disks to the right pole, as shown in Figure 2.1.
8. For n disks, the optimal solution path is 2^{n-1} moves.
9. The game ends when all disks are moved to the right pole.

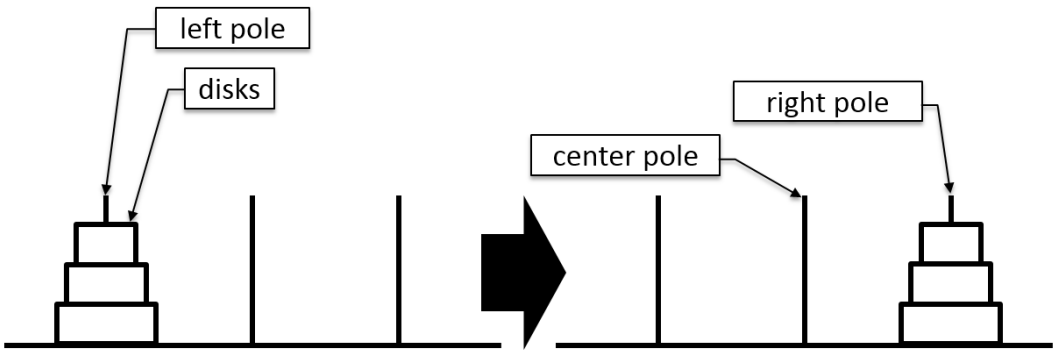


FIGURE 2.1: The ToH experimental task.

The new hypothesis consists of the procedure of trial and error. Players acquire particular strategies by trial and error method in the ToH puzzle. These trials contribute to the final solution to reproduce the completed moving procedure. The optimal number of movements for the three disks in the ToH puzzle is seven; however,

if the frequency of the trial and error decreases, the thinking process regarding executive function shifts to a working memory task instead. This process depends on the ability of the executive function.

The planning ability is enhanced by the trial and error method. In this case, the planning time would be longer than that for working memory. The brain regions associated with executive function activate if a player is making plans for a long time.

After that, this process would shift to a working memory task. Due to the complexity of the task, players cannot memorize the whole process. Players can memorize patchy rules of the solving process. Hence, those disjointed rules act in wide-area memory regions.

In the main experiment, participants learned the ToH task for seven weeks. The frequencies of button presses and achievements were recorded for each participant. Difficulty levels can be modified according to game times and the number of disks. In our analysis, the repeat task was prepared as a control task. In repeat tasks, participants push a button and do not play the game. Brain activities during the repeat task are independent of planning and decision-making. At the same time, the participant watches a video of a previous ToH task. This task has the same visual stimulus as the ToH task.

Moreover, participants perform these tasks without using executive functions. Thus, this repeat task is performed only by pushing a button and not playing the ToH. It is a type of dummy operation. In this case, particular responses appear in the motor and visual cortices. This analysis method uses two types of fMRI scans.

The first one is the scan of the ToH task. These data involve the use of the executive function. The other scans the repeat task image data without the executive function. Calculating differences between tasks and repeats can check the activation of executive functions.

2.3 Experimental Work

Before the experiment, the participants were interviewed about their knowledge and experiences with the ToH puzzle. All participants had some basic knowledge about the ToH puzzle. Player knowledge of the ToH was the same for the experimental baseline. Therefore, this knowledge can be defined as a social composition condition.

A screen located in front of the participant showed the ToH task. The participant solves a five-disk ToH puzzle in the experiment. The task is to play the ToH using a four-button controller, as shown in Figure 2.2. Participants can attempt to solve the puzzle on a screen using a controller, as shown in Figure 2.3. The participant lies inside the fMRI to play the ToH puzzle task while holding a controller in the right hand. The controller has four buttons, and this experiment uses the left, top, and right buttons corresponding to the left, center, and right poles in the ToH.

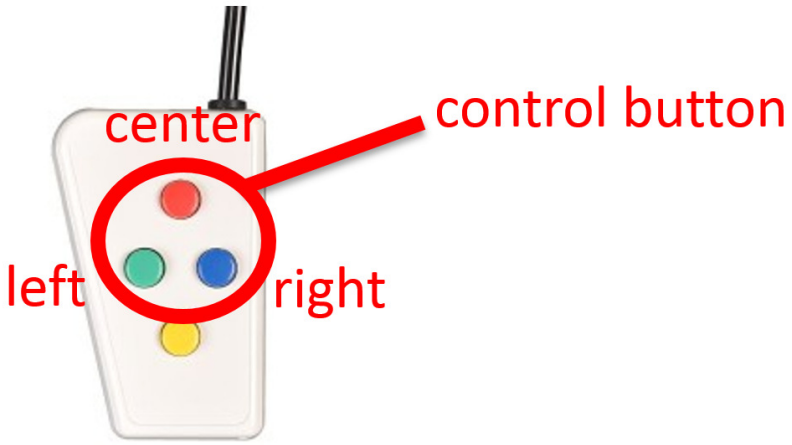


FIGURE 2.2: Controller used in the experiment while in the fMRI machine.

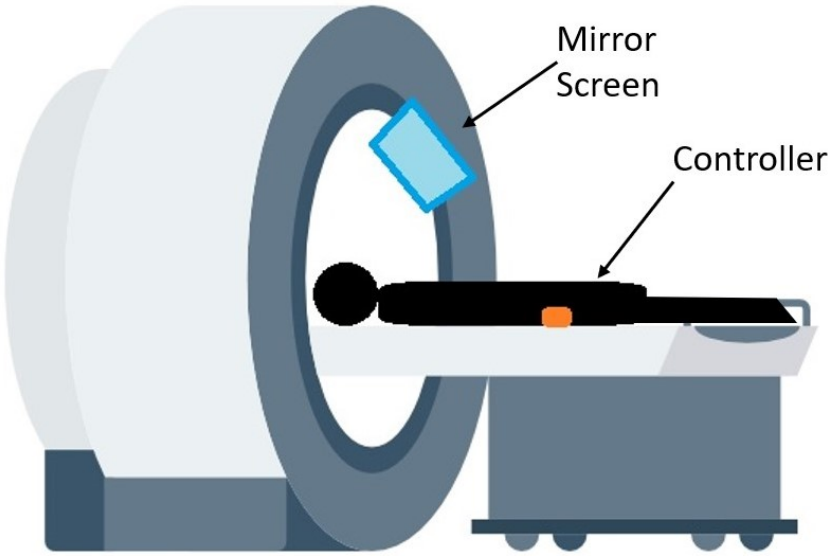


FIGURE 2.3: Mirror screen in the fMRI machine.

Participants can press a button corresponding to a pole on which disks are stacked. When the button is pressed, the disk at the corresponding pole is lifted, as shown on the left in Figure 2.4. Next, the participant can press a button corresponding to a target pole. The lifted disk moves to the target pole at that time, as shown on the right in Figure 2.4. The task is considered complete after all disks are on the right pole. Then, the disks are reset to the left pole as the initial position for the next game. Participants repeated the ToH task continuously within a given time.

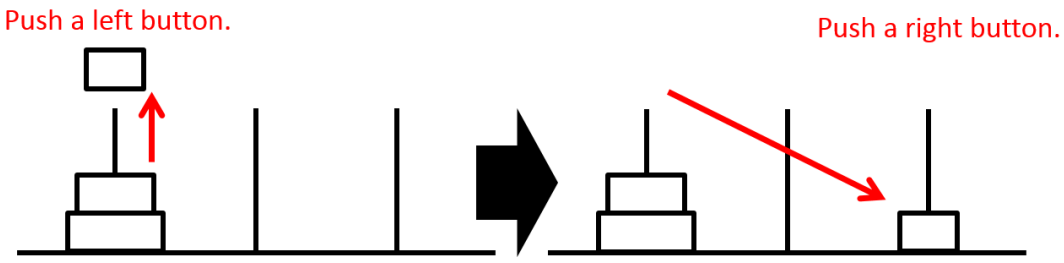


FIGURE 2.4: How to control the disks in the ToH.

Figure 2.5 shows one session of the MRI experimental sequence. This experiment consisted of three tasks and three repeats. In the Task 1 period, the task started from the initial state. The purpose was to confirm the activation associated with executive function based on activation differences between task and repeat scans. All disks

were set on the left pole as the initial position. The disk starting position in Task 2 was from the ending position in Task 1. The disk starting position in Task 3 was from the ending position in Task 2. Tasks 1, 2, and 3 only differed regarding the disk starting position. It repeated 1, 2, and 3, and a video of Tasks 1, 2, and 3 was shown. All task and repeat times were 40 s. The rest time between tasks was 10 s, and the rest time between tasks and repeats was 15 s. The total time of one session was 5 min and 40 s (136 images were scanned).

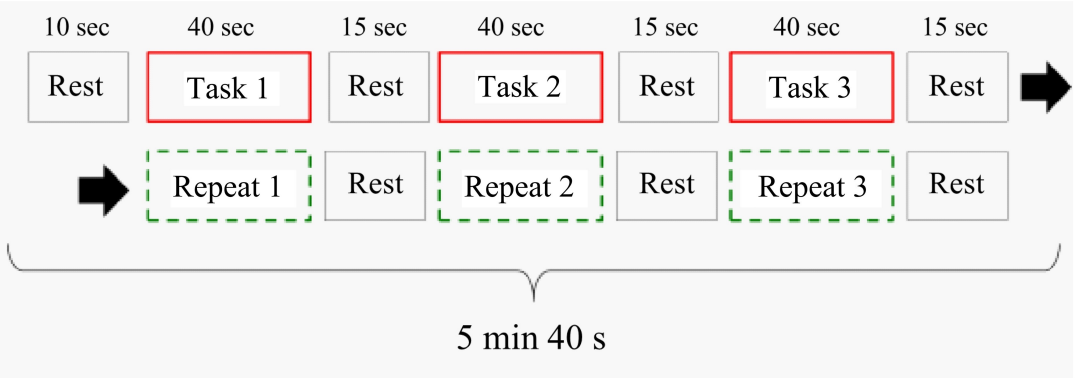


FIGURE 2.5: Task sequence during one session.

During the task period, the participant played the ToH. Participants continuously played as many times as instructed. During the task 1 period, the task started from the initial state. All disks were set on the left pole as the initial position. During the Task 2 period, the participants continued solving the puzzle from the final state of the previous task.

During the repeat period, the participants synchronously pressed the button while watching the video recorded during the task period. During this period, the push button did not affect the time performance or executive function tasks. Therefore, images during this period included only activation information in the motor and visual cortices based on controller operations. They did not have brain activation information regarding executive function, and the experiment was intended to extract only activation information. This image differed between the task and repeat blocks.

During the rest period, a fixation cross was displayed for the participant to focus. The color of the fixation cross depended on the next period. If the task period was next, the fixation cross color was red. If the next was the repeat period, then the color of the fixation cross was light blue.

In data analysis, realign (motion correction), normalize (standardization), smooth (smoothing), specify-1st-level-modeling (standard brain model determination), and estimate (brain activity grayscale images are created in the flow of the estimated activity region). By taking the difference between them, the active part is determined. Active areas are narrowed down to $p < 0.001$ significant active areas by t-test.

2.4 The Long-Term Learning Experiment Environment

The long-time learning experiment was conducted with four participants. These experiments need a longer time to process the scanning of 402 image data samples. The scanning processes cost a lot of money, and a lot of time. Therefore, finding volunteers for these types of studies is difficult. Considering all of these concerns, only four samples were tested for this experiment. However, to have a uniform study, the participants were chosen at similar ages (21–23 years old). In addition, both males and females were considered for these experiments. The attributes of the participants are as follows.

- Participant 1 was male, 21 years old, and right-handed.
- Participant 2 was male, 23 years old, and right-handed.
- Participant 3 was female, 21 years old, and right-handed.
- Participant 4 was male, 21 years old, and right-handed.

This study was approved by the Research Ethics Review Committee of Kochi University of Technology (approval number: 52-C3). All participants provided written informed consent before the experiment began. Figure 2.6 shows the experimental flow. This learning experiment was conducted for seven weeks. The participants learned to solve the ToH for 40 min once or twice a week outside the MRI. Participants 1 and 2 participated in 12 learning sessions (L1–L12 in Figure 2.6). Participants 3 and 4 participated in a total of 10 learning sessions. Though the number of sessions used to train the participants differed (10 and 12), the evaluation was done constantly. Therefore, overlearning by participants 1 and 2 can be disregarded.

To observe the participants' brain activity and progress in and convergence of learning, they underwent fMRI scans three times while solving the ToH (M1–M3 in Figure 2.6) in this experiment. fMRI scans were performed immediately after the first (L1), fourth (L4), and last learning periods (L12 or L10). The interval between M1–M2 was ten days, and the interval between M2–M3 was 30 days.

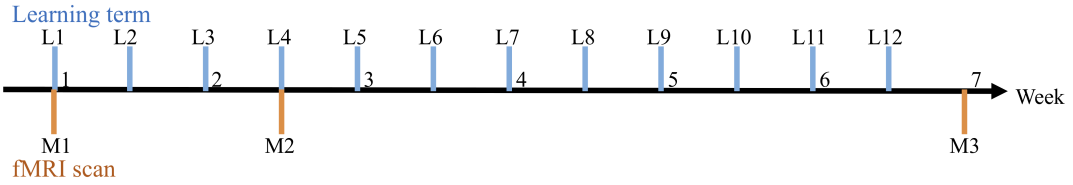


FIGURE 2.6: Experimental flow over 7 weeks.

It was used a MAGNETOM Verio 3T scanner (SIEMENS Co., Ltd., Erlangen, Germany) for acquiring fMRI images. Head movement was limited with the use of mild restraints and cushioning. The imaging parameters were TR = 2500 ms, TE = 30 ms, FoV = 192 mm^2, voxel size = 3.0 mm^3, and slice thickness = 3.0 mm. 136 scanned for analysis images per session. Two images were excluded from the analysis because the longitudinal magnetization of the tissue was unsteady.

Furthermore, an anatomical image with a resolution of 1.0 mm^3 was combined with a T1-weighted image to obtain positional information. A projector was installed outside the MRI room and projected the experimental task image on a resin

screen near the head-side opening of the fMRI device through a telephoto lens. The participants watched the images on the screen via a mirror placed over the coil above their heads.

In this experiment, the participants performed a ToH task involving five disks. Participants lying on the bed inside the fMRI machine performed the ToH task using a controller in their right hand. Participants repeatedly carried out the ToH task within a given time. The experimental design employed was a block design with alternating tasks and rest periods. Performance data during the experiment were recorded to confirm the learning progress.

Moreover, fMRI images were obtained for each learning process. The five-disk ToH task was performed inside the fMRI machine, and the time allotted for each task was 40 s. Three ToH tasks using five disks are blocks within a certain period.

Software Platform of Experiments

SPM12 software (Wellcome Centre for Human Neuroimaging, London, UK) was used to process and analyze the fMRI data. A total of 408 images (136 images for each M1, M2, and M3 instance) were obtained from three fMRI runs. The first two scan images were discarded from each fMRI- run. Thus, this analysis used 402 scan images ($408 - (2 \times 3)$ instances).

These first two scan images were discarded because the magnetization of the MRI was not in a steady state at the beginning of each scan. Functional images were corrected for differences in slice acquisition time and motion artifacts.

This analysis examined the degree of activation between the early and late stages of learning at each region of interest (ROI). The data were realigned, normalized according to the standard Montreal Neurological Institute (MNI) model, and smoothed with an 8-mm full-width–half-width Gaussian filter. MNI coordinates were used for the brain activation analysis. Only focused voxels were analyzed using the WFU PickAtlas toolbox for masking [35, 36].

2.5 Results

The degree of progress was the learning level indicator for all participants. The calculation method for the degree of progress is as follows.

The first step was to find the shortest number of moves remaining on all the boards. The minimum number of moves for the 5 disks was 31 from the initial position, and the minimum number of remaining movements is less than 31 moves from the other starting position. One point was added to the degree of progress when the remaining operations decreased by one step. If there was no change in the remaining operation, the degree of improvement remained the same. Conversely, one point was subtracted from the degree of progress when the remaining operations increased by one step. Therefore, the total possible score when solving a puzzle was 31 points. The remaining operation was assumed to be a measurement of the learning level. The point calculations are shown in Figure 2.7.

Card's MHP defines the fastest time a person can press the button as approximately 0.3 s [28]. In this case, since the time for one task, was 40 s, the maximum number of evaluation points was about 130 (=40/0.3). If there are few remaining operations in the task, the degree of progress is a high score. In this case, a high score indicates a quick and accurate operation. Therefore, in this case, the learning level of the participant is high. The degree of progress is calculated to evaluate the

learning level for the task.

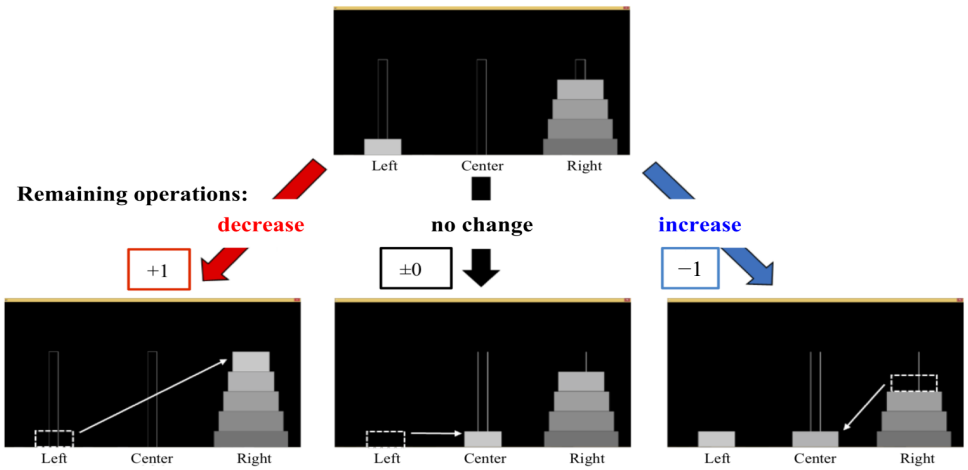
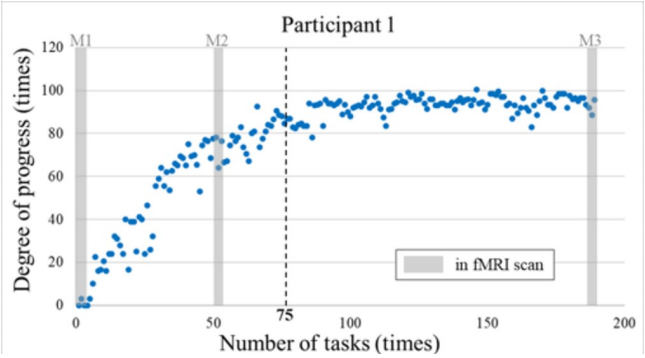


FIGURE 2.7: The evaluation method for the degree of progress.

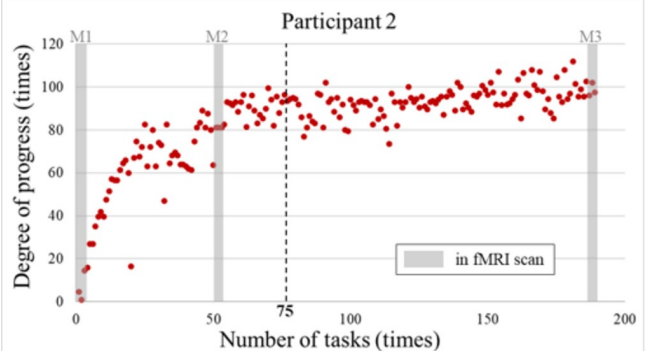
The participants completed the tasks between 150 and 180 times and underwent fMRI scans nine times. The degree of progress was calculated for each job. Figure 2.8 shows the learning curves for the degree of improvement for each participant. Their transitions can be confirmed based on the learning curves.

The learning curves converged after Task 75 (in L5). The gray part shows corresponding marks about the data from the fMRI scans (M1–M3). The observed learning progress for M1 and M3 are at the beginning and end areas of the learning period, respectively. Moreover, their learning was progressing in M2.

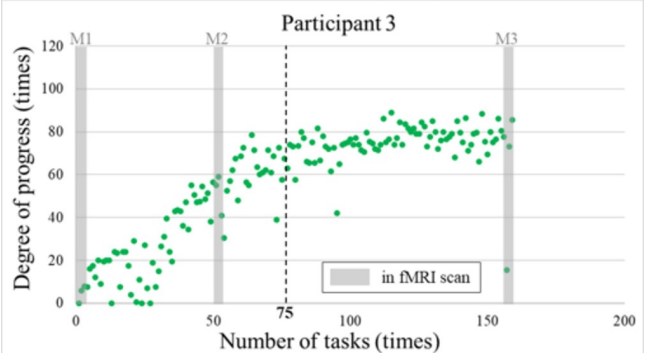
Four ROI masks were used for the DLPFC, parietal lobe, inferior frontal gyrus, and premotor areas. Several examples show an increasing or decreasing trend in brain activity as learning progresses [37, 38]. There is a close relation to the learning behavior of brain regions that show such increasing/decreasing trends. In the first analysis, we observed differences in brain activity between the whole brain's first and third fMRI scans. We searched for brain regions (voxels) that showed significant differences. We examined the relationship between learning progression and the activity level of each scan for the regions that showed significant differences in brain activity. We designed the contrasts and analyzed the brain activity on the SPM to verify this significant difference. The contrasts were "first fMRI scan vs. third



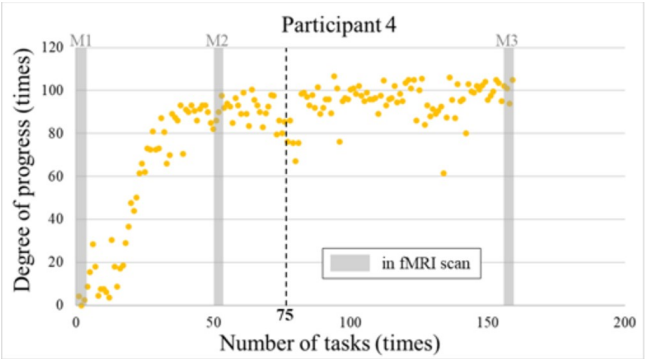
(**a**)Learning curve for Participant 1.



(**b**)Learning curve for Participant 2.



(**c**)Learning curve for Participant 3.



(**d**)Learning curve for Participant 4.

FIGURE 2.8: Learning curve for the degree of progress.

fMRI scan" and "third fMRI scan vs. first fMRI scan". These fMRI scans consisted of all tasks vs. all repeats in the same session. Statistical thresholds were set for uncorrected brain peak levels ($p < 0.001$) and corrected cluster levels ($p < 0.05$). For motion correction, all models included the six-dimension head-motion parameters as the regressor.

Executive function is critically dependent on PFC activation [11, 15–22]. The PFC is believed to be involved in planning ability [2, 39, 40].

2.6 Discussion

Previous studies have confirmed the activation of the DLPFC (BA 9) in the ToH task. On the other hand, some researchers have argued for the activation of the parietal lobe (BA 7, 40), inferior frontal gyrus (BA 44), and premotor cortex (BA 6) [23–27]. These studies suggest that these brain regions are involved in planning ability. Investigations of these brain regions focus on the transition of brain activity at the peak coordinates in each task.

Moreover, investigations of differences in activation have focused on these regions in each participant. Table 2.1 shows the location of the brain regions with the maximum difference in activation between the first (M1) and third fMRI scans (M3) for each participant. Figure 2.9a–d shows the degree of brain activity for each of the three tasks (M1, M2, and M3) in the experimental flow. The reports of brain activation were indicated with signal plots for the DLPFC, premotor cortex, parietal lobe, and inferior frontal gyrus. All signal plots show activity under the experimental condition (event type) relative to baseline (in arbitrary units [a.u.], $\pm$90% confidence interval). The plots show activity patterns at the peak of activation (i.e., single voxel) as selected from the whole-brain contrast SPM map.

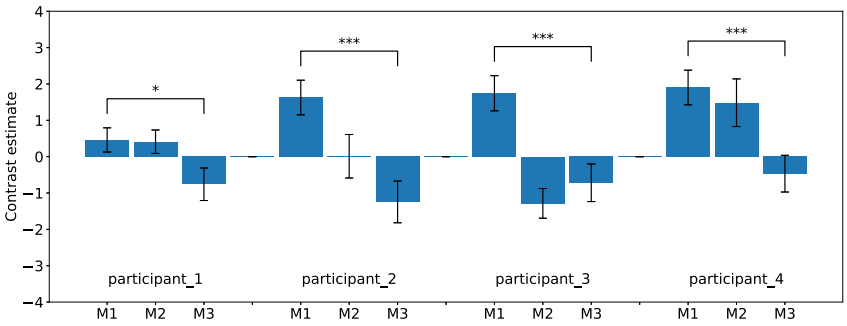
Performance data showed that each participant's learning curve converged at the 100th and 150th tasks. The goal of this task was to observe only the brain activity

related to executive function in each learning period. Reports have shown that executive function is closely associated with the parietal lobe and cerebellum, especially the PFC. The PFC has involved the establishment of target behaviors that are necessary for executive function. Environmental dependence is also said to be involved in goal maintenance. Moreover, conservation is involved in the flexible changing of goals.

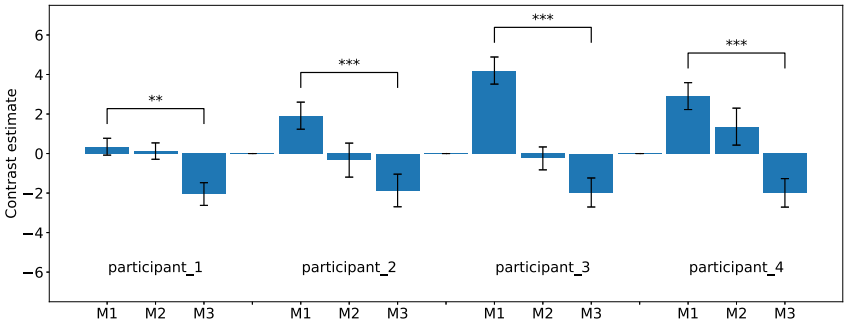
TABLE 2.1: Peak coordinates with the most differences in activation

Region label	Participant No.	L/R	MNI coordinates		
			x	y	z
Parietal lobe	1	L	-22	-10	72
	2	L	-4	6	66
	3	R	38	10	60
	4	L	-22	-2	66
Inferior frontal lobe	1	R	44	-70	48
	2	R	58	-24	14
	3	L	-26	-66	52
	4	L	-30	-50	62
Premotor cortex	1	L	-32	34	36
	2	L	-8	26	34
	3	L	-40	46	32
	4	L	-44	32	34
Dorsolateral prefrontal cortex	1	R	58	16	18
	2	L	-60	16	12
	3	R	46	16	14
	4	R	52	12	8

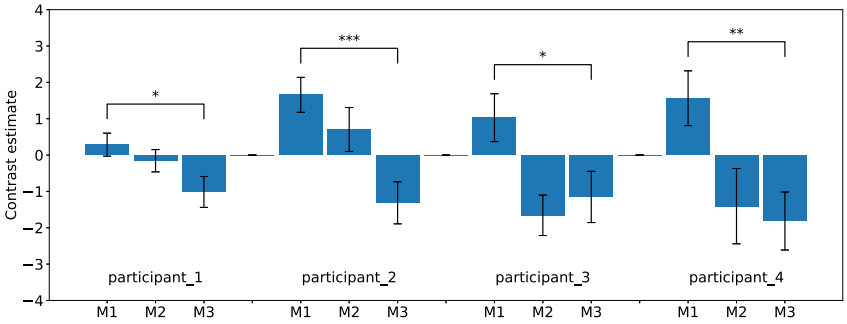
Based on the results of the fMRI analysis, differences in activation were observed in the DLPFC (BA 9), parietal lobe (BA 7, 40), inferior frontal gyrus (BA 44), and premotor cortex (BA 6) in each participant. Comparing the brain activities during M1–M3, the differences followed decreasing trends. These brain regions are involved in



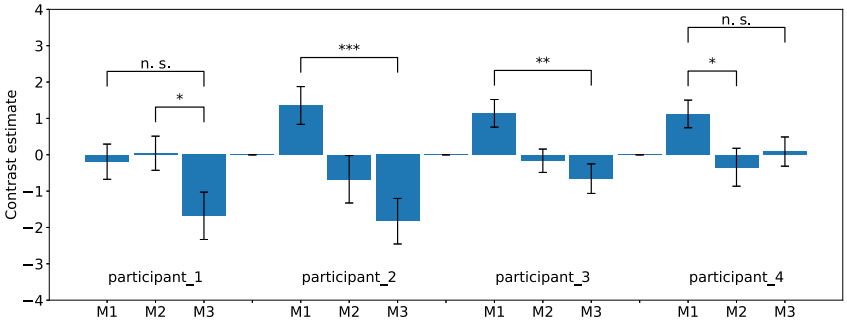
(**a**)Trends in brain activity in the premotor cortex.



(**b**)Trends in brain activity in the parietal lobe.



(**c**)Trends in brain activity in the dorsolateral prefrontal cortex.



(**d**)Trends in brain activity in the inferior frontal gyrus.

FIGURE 2.9: Trends in brain activities in different locations of the brain. For all plots, the $Mean \pm SE$ is displayed. Asterisks indicate P-values (n.s. $P > 0.05$, *$P \leq 0.05$, **$P \leq 0.01$, ***$P \leq 0.001$ for the two-tailed Welch's t-test).

the executive functions of complex behaviors, goal maintenance, flexible goal modification, and a combination of goals [2, 23–27, 39, 40]. There have also been reports of decreases in related brain region activity as learning progresses [38, 41, 42].

Furthermore, the performance results in this experiment confirmed a convergence of the learning curve. We believe that the participants were in a state where they had completed sufficient learning and could perform efficiently.

In the fMRI data, brain regions involved in executive functions showed a decrease in brain activity after learning relative to before learning. This result suggests that the participants efficiently performed task anticipation, planning, and decision-making.

On the other hand, several other studies employing the ToH task have reported that the frontal pole is related to executive function [19, 29]. However, the results of this experiment, which measured differences between pre-and post-learning, found no differences in the activation of this region.

This result suggests that there is not much effect on short-term learning for the frontal pole. Hence, long-time learning performed with trial and error increases brain activity.

Chapter 3

Commonality and Specificity of Brain Activity Patterns Represented by the Evaluation Criteria

3.1 Introduction

Human decision-making, both simple and complex, occurs hundreds to thousands of times per day. A few examples may include decisions such as “What to eat”, “Which clothes to wear”, and “How to solve a problem”. Among these scenarios, purchase decision-making is a familiar and frequently encountered decision. When buying a product, especially a more expensive one, people tend to compare information to aid in the decision-making process. In recent years, online shopping has given people the opportunity to purchase a greater variety of products. However, due to the large variety of product lineups, it is difficult to make the best decision that satisfies consumer requirements. Furthermore, consumers cannot check the actual products, only view the product information, images, and reviews displayed on the screen. Therefore, decision-making regarding the purchasing of products should

be supported. An important step in this direction would be to elucidate brain representation to gain a better understanding of the human decision-making process.

One area that has been repeatedly shown to be activated by diverse rewarding stimuli is the vmPFC. In several neuroimaging studies, this brain region is active for a variety of primary and abstract rewards, including sports cars [43], cola preferences [44], pleasant odors [45], wine prices [46], facial attractiveness [47] and money [48]. The results of these past studies support the idea that the vmPFC is involved in converting the values of diverse stimuli into a common measure for a behavioral choice. Other findings have suggested that product preference activates the nucleus accumbens (NAcc). Knutson et al. [49] reported that preference elicits NAcc activation before a purchasing decision, whereas excessive prices can elicit insula activation and medial prefrontal cortex (MPFC) deactivation.

Multi-voxel pattern analysis (MVPA) considers external stimuli, motion state, and mental content to be encoded in brain activity patterns. MVPA can save and distinguish spatial response patterns lost by averaging the responses across voxels in the ROI, as in univariate analysis. When detecting the presence of a specific cognitive condition in the brain, the main advantage of MVPA is its increased sensitivity. The conventional fMRI analysis attempts to find voxels that exhibit statistically significant responses to experimental conditions. To increase the sensitivity to certain conditions, these methods spatially average the voxels that respond significantly to that condition. Although this technique reduces noise, it also reduces the signal in two important ways. First, a voxel with a non-significant response to a particular condition can carry some information about the presence/absence of that state. Second, spatial averaging can blur the spatial pattern that distinguishes experimental conditions. As with conventional methods, the MVPA approach also attempts to increase sensitivity by looking at the contributions of multiple voxels. However, to avoid the signal loss problem mentioned above, MVPA does not routinely involve

a uniform spatial average of the voxel response. Instead, it uses a weighted average of responses that treat each voxel as a separate source of information about the participant's cognitive state. This technique optimizes these weights and aggregates this information among voxels and finds ways to guide participants more accurately in terms of what they are thinking [50]. With this method, by analyzing a pattern composed of multiple voxels, it was possible to explore the brain expression of detailed information that could not be examined by conventional fMRI analysis. The traditional univariate approach focuses on the activity changes of each voxel. By contrast, MVPA extracts information from many brain locations (voxels) at the same time to examine the spatial brain activation pattern. MVPA is often used for neural decoding. Neural decoding is a technique to estimate stimuli, behaviors, and cognitive states. Several neural decoding studies are being conducted to reconstruct visual information, cognitive judgments, and emotions [51–53]. Machine learning methods such as the support vector machine and neural network are important for this approach. Neural decoding is realized by learning brain activity patterns, which are multidimensional variables, using a machine learning algorithm and outputting prediction values from new brain activity patterns using the learned model. There are many studies on biometric data classification using machine learning other than neural decoding. In the medical field, research is being conducted to detect lesions and classify benign/malignant tumours, and machine learning methods are used [54, 55].

Given this background, the present study aimed to estimate user choice in decision-making based on brain activity. To achieve this aim, we experimented to verify the brain regions involved in the evaluation criteria in decision-making processes and investigated the representation of their categories using fMRI and MVPA. Assuming

a situation involving the purchase of smartphones through online shopping, participants picked one from a choice of two products with information for a single evaluation criterion. This task involved four types of evaluation criteria for decision-making. We focused on the voxel pattern in ROIs based on differences in the type of evaluation criteria. To our knowledge, brain regions reflecting the type of evaluation criteria used in decision-making have not been reported.

We hypothesized that the type of evaluation criteria is specific to or commonly involved in certain brain regions. This analysis focused on the vmPFC, insula, and NAcc, which are considered to be involved in decision-making and were used as ROIs[56–60]. We hypothesized that there would be a difference in the activation patterns of the vmPFC, insula, and NAcc depending on the type of evaluation criteria. To examine this hypothesis, a decision-making task regarding each evaluation criterion was performed. Differences in brain activation patterns due to the differences in evaluation criteria in these ROIs were then examined by comparing each combination of evaluation criteria. For the analysis, we used MVPA, which has been established as an effective method for identifying and classifying brain activity patterns. Based on different evaluation criteria, the voxel patterns from all associated regions were examined using MVPA. Each combination of the four evaluation criteria was analyzed after binary classification by MVPA. Finally, based on the binary classification accuracy obtained from MVPA, the regions among the ROIs that reflected differences in evaluation criteria were evaluated.

For many people, evaluation criteria such as price, color, and production date are important factors in making a better purchase. The results obtained in this experiment indicate that vmPFC and NAcc respond concerning the same endpoints when making a choice. Moreover, as shown in [46, 49, 56, 57, 59], the vmPFC and NAcc are sites involved in decision-making and execution. On the other hand, there are neuromarketing methods that take advantage of findings from brain science and apply them to marketing activities [61–63]. It is important to analyze consumer psychology

and behavioural principles indicated by brain science. The traditional methods of behaviour analysis were questionnaires or interviews and thus could not elicit consumers' unconscious true intentions. However, the results of this research proved that the vmPFC and NAcc measurements can be used as a model to visualize and quantitatively evaluate consumers' unconscious psychology and preferences, which are difficult to verbalize.

3.2 Materials and Methods

3.2.1 Participants

Twenty-five participants (five females; two left-handed; mean age 20.60 years, standard deviation 1.26 years, age range 19–22 years) participated in the fMRI experiment. One participant who did not complete the experiment was excluded. Therefore, 24 participants were finally included in the data analysis. This study was approved by the Research Ethics Review Committee of Kochi University of Technology (approval number: 52-C3). All participants provided written informed consent before the experiment began.

3.2.2 Task and Stimuli

All participants performed a decision-making task that involved choosing a smartphone by referring to each evaluation criterion. Fig 3.1 shows the experimental timeline. This experiment is based on a block design. It consists of several discrete periods of on–off blocks, with the "on" representing a task condition, and the "off" referring to a rest state or different task condition.

In this task, participants viewed a screen, an example of which is illustrated in the lower part of Fig 3.1. The screen presented two identical smartphone images and the letters of each different combination of evaluation criteria as stimuli. This experimental design using these stimuli, which are illustrated in two identical images, each

with different information, has also been adopted in other decision-making studies [64]. The participants pushed the left or right button to select the smartphone they wanted more.

The experimental conditions included the price, body color, and production year as the evaluation criteria. The body color evaluation was conveyed through textual information instead of an illustration. The reason for this was to avoid the possibility of a difference in willingness to purchase depending on the displayed color of the product [65]. These choices were selected as evaluation criteria because they can be evaluated easily regardless of the presence or absence of smartphone knowledge among the participants. In addition, a dummy variable (four squares as meaningless symbols) was set as the control condition. Brain activity at the time of the main task was considered to include three main effects: decision-making, visual recognition of the stimuli, and button-pressing at the time of selection. In addition, brain activity during dummy tasks is thought to reflect the effects of almost the same condition as the main task, except for decision-making. Brain activity regarding the difference between the main and dummy tasks is considered to represent only the effects of decision-making. Each criterion had four types of content. Table 3.1 shows the list of evaluation criterion labels used in this experiment. Each participant was considered to have a different priority for each evaluation criterion. In this experiment, it was hypothesized a specific brain-related region would refer to the impression for each evaluation criterion that included priority differences. The evaluation criteria appeared in a different order for each participant. Each participant performed two runs under the same conditions. Each run contained eight blocks of four separate tasks: the price choice, the color choice, the year choice, and the dummy choice. During each choice, a screen showed information for 3 seconds followed by a rest period for 2–4 seconds. The screen presented two images of the smartphone, shown on the left and right of the screen. Different labels under the images represented each evaluation criterion. In the choice tasks, the participants decided on an object

in their mind, and then pushed the left or right button to select the object they had chosen. In the dummy tasks, the participants were required to push either button intuitively. The total time of one run was 306 seconds. Stimuli images and words were rear-projected onto a screen placed in the scanner bore using an LCD projector. The screen showed two identical smartphone images and two different labels as an evaluation criterion, as demonstrated in Fig 3.1.

TABLE 3.1: List of evaluation criterion contents

Evaluation criteria	**Labels**			
Price	¥10,000	¥15,000	¥20,000	¥25,000
Color	Black	White	Red	Blue
Year	2004	2008	2012	2016
Dummy	□□□□			

Note: ¥ sign means Japanese yen.

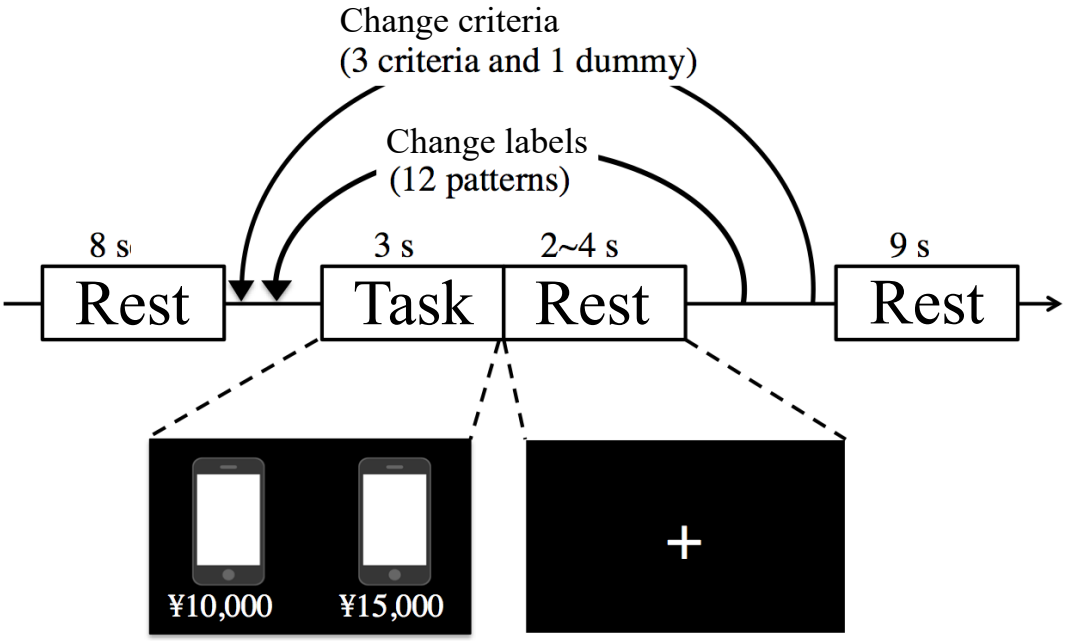


FIGURE 3.1: Experimental timeline.

3.2.3 MRI Acquisition and Data Preprocessing

Scanning was performed on a 3.0-tesla scanner (MAGNETOM Verio, Siemens Healthinners, Erlangen, Germany) using a 16-channel head coil at the Kochi University of Technology. Functional scans were acquired with a standard gradient-echo echo-planar imaging sequence to cover the whole brain (field of view = 192 mm^2; repetition time = 3,000 ms; echo time = 30 ms; flip angle = 90 degrees; slice thickness = 3.0 mm; voxel size = 3.0 mm^3). Each run of the functional scans obtained 102 volumes over a total duration of 306 seconds. A high-resolution T1-weighted anatomical scan was acquired for each subject (1.0 mm^3 resolution).

The first two scans (6 seconds) in each run were discarded to account for any instability with the fMRI scanner. SPM12 software (Wellcome Centre for Human Neuroimaging, London, UK) was used to process and analyze the functional data. Functional images were corrected for differences in slice acquisition time and motion. The data were then realigned and normalized to the Montreal Neurological Institute (MNI) standard brain model. The brain activation degrees were analyzed on the MNI coordinates.

3.2.4 fMRI Analyses

The following four conditions were modelled: price choice, color choice, year choice, and dummy choice. Common or specific brain regions were involved in each condition, and these regions were identified by creating contrasts. With the first level (single subject analysis), contrasts (price vs. dummy, color vs. dummy, and year vs. dummy) were created to identify brain regions, which were commonly activated for all contrasts. Price choice vs. the two other choices, color choice vs. the two other choices, and year choice vs. the two other choices were created to identify brain regions, which were specifically activated for each contrast. With the second level (group analysis), one sample t-tests were performed to examine significant brain activation among the group during the contrasts mentioned. A statistical parametric

map was generated using the price, color, and year vs. dummy choice contrasts. Clusters of voxels were corrected for multiple comparisons across the whole brain using family-wise error correction and a threshold of p-values: $p < 0.05$ [66]. The statistical parametric maps were generated using color vs. (price & year) choice contrast. Clusters were defined using a height threshold of $p < 0.001$ uncorrected for multiple comparisons with a cluster size threshold of $k = 171$ voxels. In the contrasts of price vs. (color & year) and year vs. (price & color), no suprathreshold clusters were applied.

3.2.5 Multi-Voxel Pattern Analysis

The results of the fMRI analysis described in the previous section showed activation in the vmPFC during decision-making about each evaluation criterion. Brain activation patterns in the decision-making task were investigated using MVPA based on each evaluation criterion.

MVPA was performed using a support vector machine (SVM) with a linear kernel [67], as implemented in the Pattern Recognition for Neuroimaging Toolbox [60]. The pattern analyses were performed separately for each participant. The β value at decision-making based on each evaluation criterion obtained from the general linear model in the previous section was taken as the input value. There were 48 β belonging to four evaluation criteria, including the dummy, from two runs for each participant (24/run). Binary classification according to the four evaluation criteria was carried out, with each *beta* representing a single decision-making event based on an evaluation criterion. As the evaluation criterion for each β is already known, in MVPA, these *beta* values were labelled "price", "color", "year", and "dummy". The *beta* values, which were labelled as two types of evaluation criteria, were input to the SVM as training sets to generate a boundary of two classes. We examined into which class the sample data with either label were classified.

The analysis was performed using voxels in only the vmPFC, insula, or NAcc by masking using the PickAtlas toolbox. In this analysis, binary classification by SVM was performed to test whether every ROI could distinguish between the four evaluation criteria (e.g., "price or color", and "color or year"). WFU PickAtlas [35, 36] was used to create the three ROI masks for the vmPFC, insula, and NAcc. The mask for vmPFC selected the Brodmann areas 10, 14, 25, and 32 as defined by Finger [68]. Data were cross-validated using the leave one block out method, with two sets of 24 data points from each participant. Only one sample data point was extracted from all data as a test set. The remaining data points were used as a training set. The verification was repeated using all sample data as a test set. The number of correct answers among the 48 data points by each participant (e.g., when price data were classified as price) was obtained from the SVM. Next, the average correct answer rate for each binary classification obtained from all participants was calculated. The average correct answer rates were evaluated to reveal whether the brain activity pattern of each ROI expressed the evaluation criteria for decision-making.

3.3 Results

3.3.1 Whole-Brain Analysis Results: Common and Specific Brain Activity Regions

We performed a whole-brain analysis to identify regions that have common significant activation in each choice. Table 3.2 shows MNI peak coordinates in each contrast, which are price vs. dummy and color vs. dummy, year vs. dummy. MNI peaks were reported for voxels at $p < 0.05$ FWE corrected for multiple comparisons; L = left and R = right hemisphere. Significant differential activities in the contrast of price vs. dummy were observed in the left occipital gyrus and right calcarine. In the contrast of color vs. dummy, significant differential activities were observed in the left fusiform gyrus, bilateral occipital gyri, right lingual, bilateral superior frontal

gyri, left insula, right cerebellum, left triangular part of inferior frontal gyrus, right calcarine, right middle frontal gyrus and right angular. In the contrast of year vs. dummy, significant differential activities were observed in bilateral occipital gyri, right inferior temporal gyrus, and right cerebellum.

TABLE 3.2: Common significant brain activation in each contrast

Region Label	Cluster size	T-statistic	MNI Coordinates		
			x	y	z
Price vs. Dummy					
Occipital Mid L	482	9.35	-22	-96	0
Calcarine R	363	8.80	24	-92	2
Color vs. Dummy					
Fusiform L	484	8.94	-40	-54	-10
Occipital Inf R	59	8.41	36	-84	-12
Lingual R	91	8.01	12	-90	-4
Frontal Sup Medial R	15	7.60	6	24	42
Occipital Mid R	31	7.38	32	-66	26
Insula L	16	7.13	-30	18	-4
Cerebellum 9 R	5	6.90	6	-56	-40
Frontal Inf Tri L	4	6.83	-38	38	10
Calcarine R	7	6.83	6	-62	12
Occipital Sup R	8	6.81	30	-72	46
Frontal Sup 2 L	1	6.78	-12	50	38
Frontal Mid 2 R	1	6.75	36	52	-2
Occipital Mid L	24	6.67	-30	-78	24
Frontal Mid 2 R	1	6.53	30	54	4
Occipital Mid L	1	6.50	-28	-80	18
Angular R	1	6.44	34	-70	46
Year vs. Dummy					
Occipital Inf L	464	10.26	-38	-82	-10
Occipital Inf R	527	9.80	22	-92	-4
Occipital Mid L	23	7.69	-30	-80	24
Temporal Inf R	19	6.95	50	-64	-12
Cerebellum 6 R	1	6.45	10	-74	-18

Note: Region labels were named on the basis of the automated anatomical labelling (AAL) template [69] which is a software and a digital human brain atlas with a labelled volume. The labels indicate macroscopic brain structures. Cluster size is reported in voxels. The T-statistic value is the total average, which was calculated for each voxel from the MRI data of each subject, divided by the standard deviation of all subjects.

Significant activity was observed commonly for all the contrasts only in the occipital gyrus. Figure 3.2 shows the significant activities in the occipital gyrus (coordinate: z = -12) of price choice, color choice, and year choice versus dummy choice

($p < 0.05$ corrected).

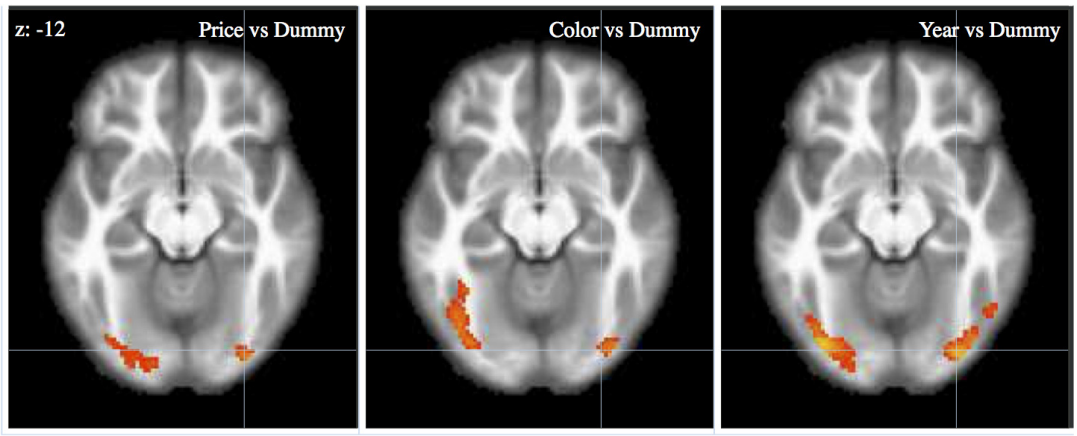


FIGURE 3.2: Brain regions with stronger activation in response to price vs. dummy, color vs. dummy, and year vs. dummy.

The difference in price, color, and year choice on bilateral occipital gyri were investigated. Firstly, a contrast of (price & color & year) vs. dummy was set to determine the voxel (coordinate) for comparing activation degree. Then, activation degrees among the price, color, and year choice were compared on the same voxel of the determined coordinate. As a result of the analysis of this contrast, the peak coordinate of significant activation was located (32, -86, -12) and (-40, -80, -10) in bilateral occipital gyri. In these two voxels, brain activation degrees during each choice (price, color, year, and dummy) were calculated. Figure 3.3 shows activation degrees during each choice on left and right occipital gyri. The occipital gyrus is located in the visual cortex, therefore this activity was considered a possible influence by seeing the stimulus. However, brain activation degree during the price, the color, and the year choice were significantly higher than the dummy choice, this brain activation is considered to be a decision-making activity. No significant activation difference was observed among the price, the color, and the year choice.

In addition, specific significant activation in each choice was investigated. The results of color vs. (price & year) are depicted in Figure 3.4 and the peak coordinates are given in Table 3.3 ($p < 0.001$ uncorrected, $k = 171$). In this contrast, the left inferior frontal gyrus, right precuneus, and left occipital gyrus had significant activation.

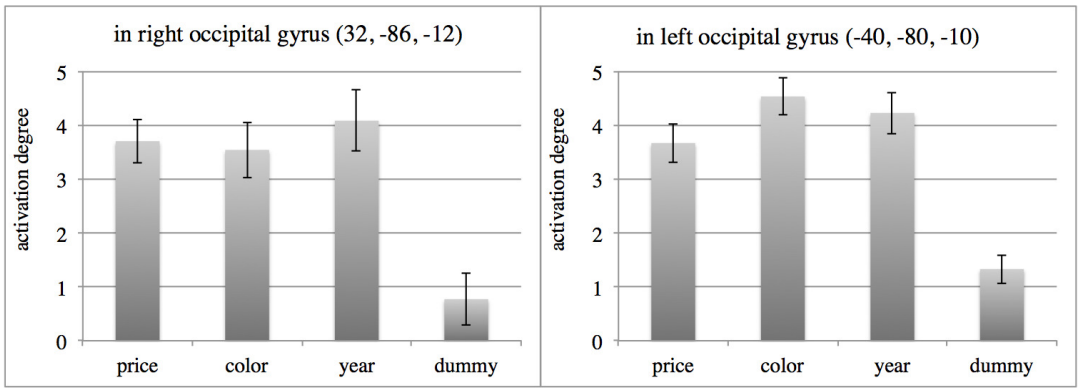


FIGURE 3.3: Activation degree during each choice, left: right occipital gyrus, right: left occipital gyrus

There was no significant activation in the contrasts of price vs. (color & year) and year vs. (price & color).

TABLE 3.3: Specific significant brain activation in color vs. (price & year)

Region Label	Cluster size	T-statistics	MNI Coordinates		
			x	y	z
Color vs. Price and Year					
Frontal Inf Tri L	1531	6.37	-34	38	12
Precuneus R	1312	5.51	8	-56	44
Occipital Mid L	171	5.21	-36	-80	14

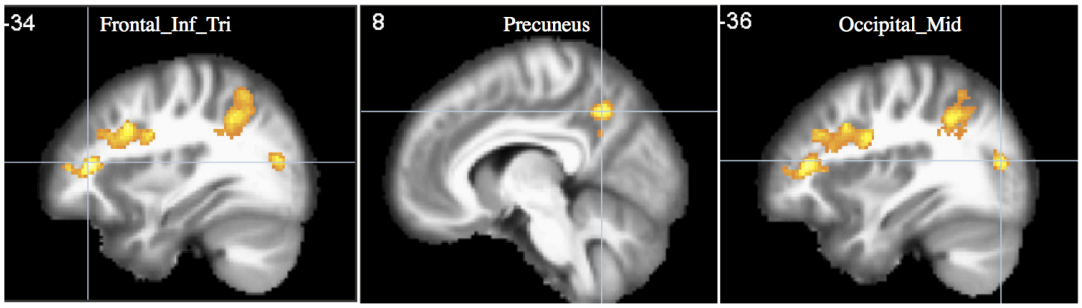


FIGURE 3.4: Brain regions with stronger activation in response to color vs. price and year.

3.3.2 ROI-Analysis Results: Brain Activity in the vmPFC

In the analyses of common and specific brain activity regions, significant activation in vmPFC was not observed, so ROI analysis was performed for the purpose of identifying differences among each choice in the vmPFC. The ROI analysis used the

Brodmann area 10,14, 25, and 32 defined by Finger [68] as the region of vmPFC in the PickAtlas toolbox [35]. Figure 3.5 shows the significant activation in vmPFC during price, color, and year choice from the ROI analysis. The regions with strong activation in each condition are projected in the three views and the color intensity indicates the brain activity strength. These peak coordinates were given in Table 3.4 ($p < 0.001$ uncorrected). Significant activation was observed on vmPFC during each choice. In the price choice, a cluster with strong activation was observed (shown by the red circles in the left part of Figure 3.5). In the color choice, two clusters with strong activation were observed (shown by red circles and blue circles in the middle part of Figure 3.5). In the year choice, a cluster with strong activation was observed (shown by the green circles in the right part of Figure 3.5). The color of the circle in Figure 3.5 is classified according to the approximate coordinates of the activation region in vmPFC, and strong activation with similar coordinates indicated by the red circle was observed in the price and color conditions.

This result shows the possibility that detailed regions with activation on the vmPFC differ by type of evaluation criteria at the decision-making. In previous studies, there are many reports that vmPFC is involved in the decision-making or the preference selection tasks. O'Doherty et al. conducted evaluation tasks based on differences in the attractiveness of a human face. In this result, vmPFC had a significant activity when selecting a heterosexual face with a higher attractiveness [47]. McClure et al. reported that vmPFC activated significantly when participants drank a cola of more favourite brands in the case of drinking which had different preference degrees by them [44]. On the other hand, vmPFC had no activity in studies that were evaluation tasks due to differences in attractiveness for car models by Klaus et al. and selection tasks due to differences in aesthetic preferences for paintings by Vartanian et al [43, 70]. The common point of these studies, these results was brain activity during decision-making for alternatives with different attractiveness or value based on a single evaluation criterion. The results of our study are the brain

activity by the different evaluation criteria, not the brain activity by the differences in the value of each evaluation criterion.

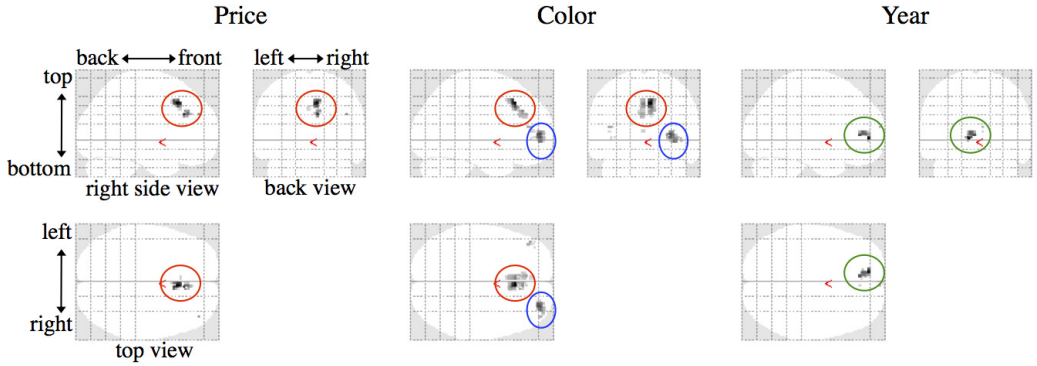


FIGURE 3.5: Brain regions with strong activation on the vmPFC.

TABLE 3.4: Significant brain activation on the vmPFC during price, color, and year choice

Evaluation Criterion	T-statistics	MNI Coordinates		
		x	y	z
Price	7.12	6	20	42
Color	7.60	6	24	42
	6.10	30	54	6
Year	4.56	-10	50	0

3.3.3 Multi-voxel Pattern Analysis Results: Brain Regions Involved in Decision-Making

The precision results for the binary classification in vmPFC, insula, and NAcc are shown in Figure 3.6, 3.7, 3.8 and Table 3.5. In these figures, the color bars represent the average value of all 24 participants, and the error bars represent standard errors. The x-axis shows a combination of each binary classification (e.g., p-c shows the result of binary classification by price and color). In the precision using the vmPFC as an ROI, the highest average accuracy was 68.40% in the dummy-color binary classification, and the lowest was 58.51% in the price-color binary classification. Regarding the result of the insula as ROI, the highest average accuracy was 58.33% in the color-price binary classification, and the lowest was 52.08% in the price-dummy

binary classification. Regarding the result of the NAcc as an ROI, the highest average accuracy was 63.37% in the dummy-color binary classification, and the lowest was 58.51% in the price-dummy binary classification.

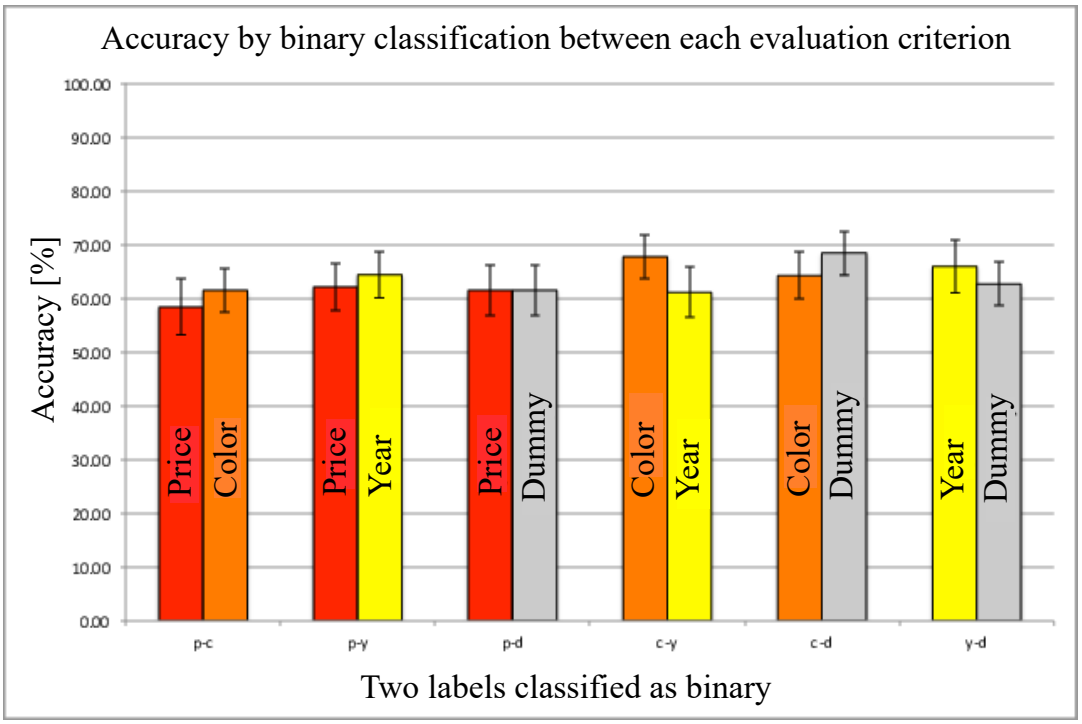


FIGURE 3.6: Correct answer rate in the vmPFC

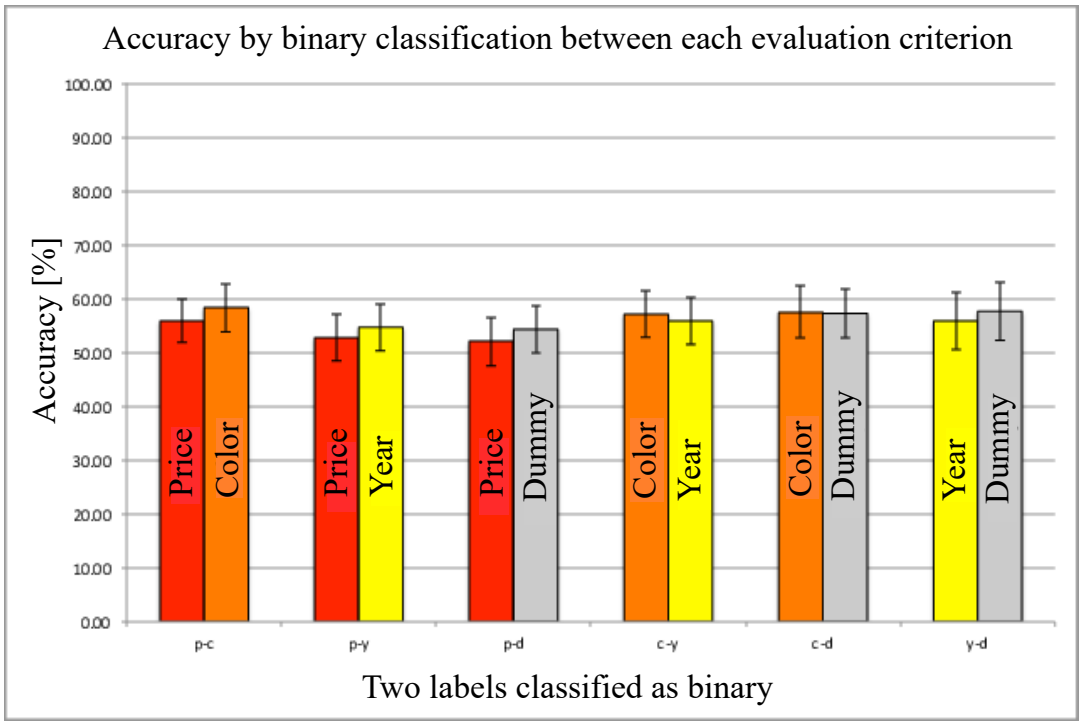


FIGURE 3.7: Correct answer rate in the insula

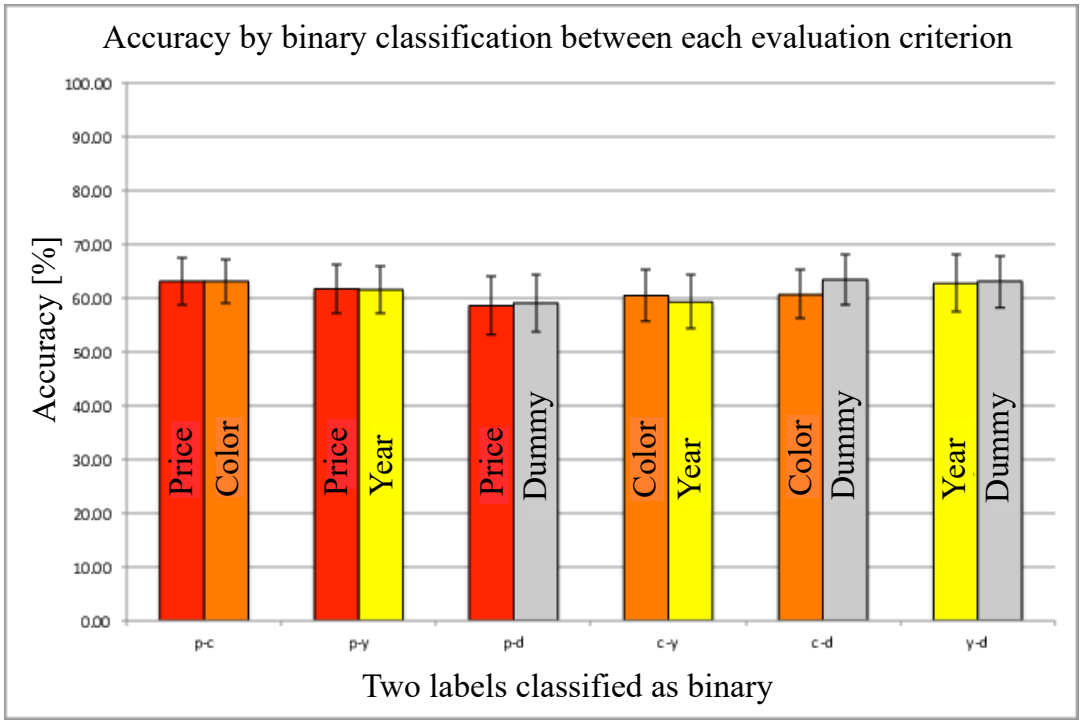


FIGURE 3.8: Correct answer rate in the NAcc

TABLE 3.5: Average accuracies and standard errors by binary classification between each evaluation criterion

Regions of interest	**Combinations of evaluation criteria**										
	p-c	c-p	p-y	y-p	p-d	d-p	c-y	y-c	c-d	d-c	y-d	d-y
vmPFC												
Average accuracy [%]	58.5	61.5	62.2	64.4	61.5	61.5	67.7	61.1	64.2	68.4	66.0	62.7
± standard error	5.3	4.0	4.4	4.3	4.7	4.8	4.2	4.7	4.4	4.1	5.0	4.1
Insula												
Average accuracy [%]	56.0	58.3	52.8	54.7	52.1	54.3	57.1	55.9	57.5	57.3	55.9	57.6
± standard error	4.0	4.5	4.3	4.4	4.5	4.5	4.3	4.4	4.8	4.7	5.4	5.4
NAcc												
Average accuracy [%]	63.0	63.0	61.6	61.5	58.5	59.0	60.4	59.2	60.6	63.4	62.7	63.0
± standard error	4.4	4.0	4.6	4.4	5.3	5.4	4.8	5.0	4.5	4.6	5.2	4.9

3.4 Discussion

3.4.1 Common and Specific Brain Regions Related to Decision-Making

This study investigated brain activation during the decision-making process of preference while using different evaluation criteria, and identified common and specific activation regions related to each evaluation criterion. As for common activation regions, the bilateral occipital gyri had significant activation during price choice, color choice, and year choice. The occipital gyrus is thought to be the brain region related to visual processing. Conversely, as for specific activation regions, the left fusiform gyrus was activated significantly during color choice. The fusiform gyrus is thought to be the brain region related to color processing [71]. Moreover, Oshin et al. reported that these regions are related to preference-rated tasks [70]. They concluded that the differential patterns of activation observed in bilateral occipital gyri and bilateral fusiform gyri in response to preference ratings are specific examples of their roles in evaluating reward-based stimuli that vary in emotional valence. However, this study investigated common brain activity by type of evaluation criteria. There is no report that the occipital gyrus and fusiform gyrus are involved in the influence on brain activity due to the difference in evaluation criteria, these results made the relationship between these gyrus functions and decision-making clearer. During color choice, the left insula was also activated. The insula is known for its involvement in value-based decision-making. It integrates the internal state, sensory signals, information about the salience, and relative value of stimuli during response selection [72]. Furthermore, the right precuneus was found to be more active during color choice compared with price and year choice. The precuneus is especially documented for its involvement in attention [73]. This suggests that the increased activation in the precuneus reflects increased attention to the color pairs compared with the price or year pairs. Therefore, it is possible that the participants made a simple numerical value comparison between the left information and the right information.

In the case of color choice, it is thought that the two color names displayed on the screen were processed based on the preference of the subjects. Therefore, it is considered that attention to color choice was higher than price and year choice, and the precuneus was activated.

The vmPFC has been shown in several neuroimaging studies to be active for a variety of primary and abstract rewards. These findings suggest that the vmPFC in the representation of complex appetitive states has several roles. However, all decision-making studies did not report that vmPFC is involved in decision-making. It suggests that the activated region differs depending on the evaluation criteria in the case of evaluating based on a value of alternative or preference by the individual. In this study, the analysis was performed based on our hypothesis that brain activity difference by evaluation criteria appears in vmPFC. Our results show that vmPFC was activated in all of the tasks by different evaluation criteria during the decision-making process. From the investigation of different activations on vmPFC for each evaluation criterion of alternatives, there were no differences in activation levels in the choice of each category. However, the activated detail regions on the vmPFC varied by each criterion. Some investigators have suggested that subjects' preference judgments stem result from "a competition between hedonic and utilitarian aspects of each choice alternative [56]", "competition between subjective emotional states such as desire and willpower [57]", "the selection of a specific dimension that enhances the contrast between the alternatives [58]", or "habit-based processing [59]". Therefore, the brain performed different processes with price, colour, and year choice. As a result, it is believed that choices by each alternative category represented brain activation on specific coordinates.

3.4.2 Brain activation patterns in the decision-making

The present study investigated the neural substrates associated with assessments of different criteria in decision-making. To this end, the study participants were presented with a pair of alternatives belonging to a single evaluation criterion and asked which product they wanted to choose based on evaluation criteria. We evaluated whether decision-making based on different evaluation criteria could be discriminated against based on the spatial activity pattern in different brain regions.

Considering the influence of the context of the vmPFC, insula, and NAcc activities observed in past studies, the ROIs of those areas were used. The vmPFC is active for a variety of primary and abstract rewards in several neuroimaging studies [56–59]. These findings suggest that the vmPFC plays several roles in the representation of complex choices, which suggests that the activated region differs depending on the evaluation criteria when based on an alternative value or preference by each individual. The insula has shown the possibility of triggering activation for the price during a purchasing decision, and the NAcc of inducing activation for individual preferences [60]. These findings suggest that the brain frames a preference as a potential benefit and price as a potential cost, thereby lending credence to the notion that consumer purchasing reflects an anticipatory combination of preference and price considerations. Although few studies have investigated the influence of differences in evaluation criteria on the brain, numerous studies have examined the influence of preferences and pleasure/discomfort when participants evaluate two or more stimuli as a decision-making task on the brain. These experimental designs are roughly divided into two types. The first is a design that presents a single stimulus in order, a design that the subject subsequently carries out in a single evaluation. The second presents a pair of stimuli at the same time, and the subjects select what they prefer more. In the present experiment, the latter design was adopted, in which the subjects evaluated a pair of alternatives belonging to a certain evaluation standard through comparisons. Numerous studies on decision-making have presented

a pair of images or character strings and performed evaluations, while others have used an experimental design that presents the same image and character strings of different contents, such as the present experimental design. Some studies have also reported results regarding activity in the vmPFC, insula, and NAcc [56, 57, 59].

As for the average accuracy of binary classification by MVPA, the present results using vmPFC, insula, and NAcc as ROIs exceeded the chance level. In the insula, even though the chance level exceeded the average precision, several combinations' standard error of the binary classification accuracy was lower than the chance level. The average classification accuracy in the insula was lower than those in the vmPFC and NAcc for all combinations of evaluation criteria. The average classification accuracy in the NAcc was about 60 %, and no difference in classification accuracy was seen for any evaluation criterion. On the other hand, vmPFC showed a difference in the binary classification accuracy for each combination of evaluation criteria. In the binary classification of price and year, the year was 2.26 % more accurate. The color was 2.95 % more accurate than the price and 6.60 % more accurate than the year. Although none of the differences in average accuracy was significant, classification in the vmPFC showed the possibility of being most classifiable when color was used as the evaluation criterion. These results suggest that brain regions involved in the decision and the preference, such as vmPFC and NAcc, represent differences in brain activity patterns in comparative decision-making.

Several studies applying MVPA to brain activity during decision-making have reported the following results. Bonnici et al. analyzed the brain pattern of the hippocampal in a simple decision-making task involving two highly similar scenes. They predicted which stimuli were being perceived under conditions of both perceptual certainty and ambiguity [74]. The classifier accuracy values of four regions on the hippocampus were above 50% of the chance level. Moreover, accuracies under the certainty condition were lower than the ambiguity condition, around 50-60%. This result has suggested that the comparison process may be occurring to reach a

decision. The alternative pairs on our choice task were unambiguous. Although the brain regions of interest were different, the classification accuracies of our results were very similar to their results under the condition of certainty. Purchasing decisions are made under both certainty and ambiguous conditions. To expand the knowledge obtained in this study, it is necessary to pay attention to the ambiguity between alternative pairs in the future. Jai et al. conducted an evaluation and bidding task for apparel products under three visual presentation conditions (static picture, zooming, or model rotation videos) and analyzed the brain patterns in "a buy decision" and "a not buy decision" [75]. By the whole-brain classification analysis, the classifier accuracy rates were 95% in the zooming and rotation conditions, while the static condition had 75%. By the searchlight classification, there were some ROIs exclusively referred by certain presentations. These results suggest that the brain regions to which various information corresponds exhibit characteristic activity patterns, and that appropriate recognition of these patterns enables classification. On the other hand, Kim et al. investigated the relationship between purchase intention and perceived garment fit when purchasing decision-making [76]. They analyzed the brain activity during the task, including the phase of evaluating the fit of the model wearing clothes and the phase of purchasing consideration with the price displayed on the clothes. As a result of the MVPA for whole brain searchlight, the classification accuracies were more than 50% of the chance level at 11 brain regions. Among them, the superior parietal lobule exceeded 80% with the highest accuracy. One of the reasons for these accuracies higher than our results may be that their tasks included multiple evaluation criteria such as garment fit and price. Our results showed that decision-making based on individual criteria is represented in brain patterns. Still, we believe that decision-making based on multiple criteria may represent more characteristic brain patterns.

This study focused on customer preferences based on individual evaluation criteria. Although the results of the classifier did not show activity patterns in specific

brain regions that depended on the evaluation criteria, they indicated the possibility that preference-based decision-making could be represented in brain patterns. It is necessary to process various factors such as reward, risk, and strategy in decision-making. In particular, regarding purchasing decisions, it is said that the factor of individual preferences produces better decisions [77–80]. The development of this research is expected to help elucidate the neural basis of decision-making and to contribute to selection, online shopping, or marketing strategies.

Chapter 4

Conclusion

In this dissertation, I described the three investigated results which are learning and representation of planning ability in the human brain involving executive function and decision-making.

Firstly, we focused on brain activity before and after learning. The effect of the planning and decision-making process concerning executive function on brain activity via long-time learning was investigated. The experimental design involved long-time learning in examining differences in cerebral activity. The participants performed individualized learning experiments involving the ToH to identify brain regions. As a result, brain regions involved in executive functions showed differences in activity between before and after learning. This study focused on the DLPFC, parietal lobe, inferior frontal gyrus, and premotor cortex as brain regions involved in executive function. Activity in these brain regions declined compared with before learning. The results indicated a conflicting trend between learning progress and brain activity.

The ability to solve the ToH requires task anticipation, planning, and decision-making. In this experiment, participant learning progressed, and their learning curves converged. Therefore, their problem-solving and task-anticipation abilities improved. Moreover, the time required for the planning and decision-making process was simplified. It was also clear that the degree of activation tends to decrease with the number of tasks, such as through M2 to M3. The frontal pole, or the PFC, is

related to the ToH task.

On the other hand, in the present long-time experiment, activation differences were obtained at the DLPFC, parietal lobe, inferior frontal gyrus, and premotor cortex after learning in each participant. We believe these activation differences were due to progressive learning about executive function.

This experiment was conducted for a long-time with only four participants due to logistic issues. Therefore, the conclusions driven by this research are not generic. More participants should be considered for sound and generalized conclusions. However, having more participants in this type of research is very challenging.

Nevertheless, we considered that the area of brain activation changes each time during long-time learning. This study analyzed behaviors and brain activities in M1–M3 in long-time learning. Exploring the dynamics of brain activity in long-time learning would also be essential. The learning curve for behavioral performance indicated this possibility.

Furthermore, a relationship with the dynamics of brain activities was observed. Various abilities are needed to solve the ToH task. The participants' learning progress from learning curves was observed during the experiments. It can be stated that the observed learning progress implies improving overall solution ability. Therefore, the dynamics of brain activity, which are associated with this ability to contribute more, should be investigated in a future study.

Next, we focused on brain activation during the decision-making process, which was selected based on a single evaluation criterion and by conducting fMRI experiments. The experiment measured brain activity during a paired comparison based on the price, color, or product year as a single evaluation criterion by fMRI, in order to elucidate the brain regions comprehensively involved in decision-making and to identify the specific brain regions involved in each evaluation criterion. From the scanned fMRI data of the choice tasks in each evaluation criterion, common brain activation and specific brain activation were performed by whole-brain analysis. The

bilateral occipital gyri had significant activation as a common activation region in choice tasks by each evaluation criterion. This result had shown that the difference in preference rate reflected the brain activity difference in the occipital gyrus.

This study investigated the common brain activity by type of the evaluation criteria, occipital gyrus was significantly activated at decision-making by all evaluation criteria. Therefore, this result suggests that the occipital gyrus is a region comprehensively related to decision-making. As for specific activation regions in choice tasks by each evaluation criterion, the left fusiform gyrus, left insula, and right precuneus was activated significantly during color choice. During price and year choice, specific activation was not observed. The results suggest that attention to color choice becomes greater compared to price or year choice. With the vmPFC, which has been reported to be involved in decision-making, significant activation was not observed from the results of the whole-brain analysis. The tasks of previous reports are decision-making for alternatives with different attractiveness or values based on a single evaluation criterion.

This study analyzed the brain activation differences among each evaluation criterion on decision-making, so these results did not focus on the differences in attractiveness or values. An ROI analysis for vmPFC was performed in order to confirm the differences the brain activation in the vmPFC by evaluation criteria. In the ROI analysis result, significant activations on the vmPFC were observed with all tasks by each evaluation criterion, and these detailed coordinates were located in different coordinates. This result suggests a possibility that detailed activity regions in vmPFC differ by the types of evaluation criteria.

Finally, we investigated the representation of evaluation criterion categories in decision-making using fMRI and MVPA. Price, color, and year were used as the evaluation criteria. We focused on the vmPFC, NAcc, and insula as ROIs.

Each combination of the four evaluation criteria was analyzed into a binary classification by MVPA. From the binary classification accuracy obtained from MVPA,

we evaluated the regions that reflected differences in evaluation criteria among the ROIs. From the results of the binary classification by MVPA, the vmPFC, and NAcc showed that these regions were capable of expressing the influence of the evaluation criteria during decision-making.

In this research, we applied classification analysis from brain activity by adopting price, color, and year as evaluation criteria because they are often involved in purchasing decisions for various products. In actual purchase decision-making, consumers also refer to various evaluation criteria. In a future study, it will be necessary to investigate brain activity patterns expressed by evaluation criteria other than those adopted in the present study and to verify whether they can be classified similarly.

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