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A Mouse-Tracking Bandit Experiment on Meaningful Learning in Weighted Voting*

Naoki Watanabe†

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Abstract

In this experiment, subjects were asked to choose one of two weighted voting games (options) repeatedly. The payoff distributions realized by subjects' choices as well as the vote apportionments and quotas of those games were hidden from them in windows on their computer screens. We mouse-tracked what information subjects viewed on the screens. The payoffs for subjects were determined by a stochastic payoff-generating function which was also hidden from subjects throughout the session. After subjects had experienced a binary choice problem in the early rounds, we examined whether those subjects increased the number of choosing the answer which would give a higher expected payoff (subjects meaningfully learned) in a similar but different binary choice problem in the subsequent rounds. The information on subjects' cumulative payoffs might promote their meaningful learning of the latent feature of weighted voting, whereas the information on their current payoffs did not, or even hindered it. It was also confirmed in a binary choice problem that the subjects who took the win-stay-lose-shift strategy (Nowak and Sigmund, 1993) paid more attention to the current payoffs and that those subjects failed in meaningful learning. We had similar findings also in the case where the subjects chose the runs of options randomly.

Keywords: bandit experiment, feedback information, meaningful learning, mouse tracker, weighted voting
JEL Classification: C91, D83, D91

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1 Introduction

When people generalized what they had learned in a situation to a similar but different one, Rick and Weber (2010) said that they learned something that underlies in those situations meaningfully; they observed that withholding payoff-related feedback information promoted meaningful learning in p-beauty contest games.[1] Even in a bandit experiment without any strategic interactions among subjects, Guerci et al. (2017) obtained the same result; subjects did not meaningfully learn the latent feature of weighted voting when they received immediate payoff-related feedback information. Feedback information is essentially incorporated in the standard theories of learning (e.g., Erev and Roth, 1998; Cheung and Friedman, 1997; Camerer and Ho, 1999). What information hindered subjects from meaningfully learning? We consider this question by mouse-tracking what information subjects actually viewed on their computer screens for their choice in the bandit experiment.

In each session of this experiment, subjects were asked to choose one of two weighted voting games (options) many times and given their payoffs which were determined stochastically by a payoff-generating function at each time. The payoff-generating function remained intact but hidden from subjects during the experiment. After subjects had experienced a binary choice problem provided in the first 40 rounds, we examined whether those subjects increased the number of choosing the answer which would give a higher expected payoff in a similar but different binary choice problem provided in the subsequent 20 rounds.

Our mouse-tracking system for this experiment was constructed in the following way. The vote apportionments provided to subjects and the payoff distributions resulting from their choice were hidden from subjects in windows on their computer screens. To open a window that hid the information subjects needed to view, they should hover their cursor over the window and click on it. The window closes when the subject moves the cursor to another window and clicks on it to view another information. Under this specification, we can measure how often or long each subject views information necessary for his or her choice without duplication of viewing time. When measuring gaze with eye trackers, subjects often unconsciously move their eye-sight to places other than the measurement targets. We could also avoid this type of noise with our mouse-tracking system.

[1] Meaningful learning is also called "transfer of learning" (Cooper and Kagel, 2003, 2008) or "epiphany" (Dufwenberg et al., 2010).

We conducted this experiment at the University of Tsukuba, where some sessions for Guerci et al. (2017) were also conducted. Each subject participated in a session in which one of four sequences of binary choice problems was examined. The main results of this paper are as follows. At the aggregate level of data, subjects learned in all binary choice problems (Result 1) and meaningfully learned in all sequences of binary choice problems except one (Result 2). It was confirmed at the individual level that the information on subjects' cumulative payoffs might promote meaningful learning of the underlying structure of weighted voting, whereas the information on their own current payoffs did not, or even hindered it (Result 3).

Guerci et al. (2017) could not observe even learning in two binary choice problems and could not observe meaningful learning by subjects in all binary choice problems, in the situation where subjects were provided with feedback information about their current payoffs immediately after their choice but were not provided with their cumulative payoffs until the end of each experimental session. Therefore, we can infer that showing the cumulative payoffs to subjects might be an important factor that generated remarkably different results between their experiment and our experiment.

Subjects might change their choices when they received zero points, but otherwise, they might not. It is plausible that subjects took this "win-stay-lose-shift" strategy (Nowak and Sigmund, 1993). It was also confirmed in a binary choice problem that the subjects who took the win-stay-lose-shift strategy paid more attention to the current payoffs and that those subjects failed in meaningful learning (Result 4). In the same binary choice problem, we had similar findings in the case where the subjects chose the runs of options randomly (Result 5). When subjects took on these types of search behavior, immediate feedback information on the current payoffs would confuse subjects' inference regarding the relationship between nominal voting weights and actual payoffs and prevented them from deeply understanding the underlying structure of weighted voting.

The rest of this paper proceeds as follows. Section 2 describes the experimental design. How mouse trackers were used is displayed there in detail. Sections 3 gives the definitions of meaningful learning and shows our results at both aggregate and individual levels of the data. The data collected with mouse trackers are analyzed at the individual level of data. Section 4 gives provides some remarks for further research.

2 Experimental Design

2.1 A Bandit Experiment in the Context of Weighted Voting

In this experiment, subjects are asked to choose one of two committees of four members who will divide 120 points among them. Let $N = \{1, 2, 3, 4\}$ be the set of members (players). A committee (a weighted voting game) is represented by $[q; v_1, v_2, v_3, v_4]$, where q is the minimum number of votes required for an allocation to be adopted (quota) and v_i is the voting weight (the number of votes) allocated to member $i \in N$. Each subject is informed that he or she acts as Member 1 but that the other members are all fictitious during the session in which they participate.

Subjects do not play the weighted voting games that they choose. In each session, the subjects face one binary choice problem for the first 40 rounds (for learning) and a similar but different one in the subsequent 20 rounds. For example, in the first 40 rounds, subjects face a choice between $[14; 5, 3, 7, 7]$ and $[14; 5, 4, 6, 7]$, while they face a choice between $[6; 1, 2, 3, 4]$ and $[6; 1, 1, 4, 4]$ in the following 20 rounds. The subjects are not informed of what binary choice problem is presented in each round. The payoffs for the subjects are determined immediately after their choice according to a stochastic payoff-generating function based on a theory of power index called the Deegan-Packel index (Deegan and Packel, 1978). The payoff-generating function is kept hidden from subjects and they are told that payoffs are determined based on a theory of decision-making in committees.

The payoff-generating function is defined as follows. Given a weighted voting game, a non-empty subset S of N is called a winning coalition if $\sum_{i \in S} v_i \geq q$. A minimum winning coalition (MWC) is a winning coalition such that deviation by any member of the coalition alters its status from winning to losing. In the experiment, one MWC is drawn with equal probability from all possible MWCs for the committee chosen by the subject. If the subject is a member of the drawn MWC, then he or she receives an equal share of the total payoff with the other members. Hereafter, we denote each MWC by the votes apportioned to its members; e.g., the MWCs in a committee $[14; 5, 3, 7, 7]$ are written as $(5, 3, 7)$, $(5, 3, 7)$, and $(7, 7)$. Member 1 belongs to two MWCs out of three, each having three members. Member 1 is thus given $120 * 1/3 = 40$ points with probability $2/3$; otherwise nothing, and his or her expected payoff is $120 * 1/3 * 2/3 = 80/3$ points.

Table 1 lists the binary choice problems we examine. For each problem, the two committees have the same total number of votes, the same quota, and the same number of votes for the subject. In terms of both expected payoffs and the set of MWCs in each choice, Problems A and C are identical, as are Problems B and D. However, there is a crucial difference between the two answers in Problems A and C. In each of these two problems, one answer has two "large" voters who can form an MWC on their own, whereas the other answer does not. In Problems B and D, there is no such clear difference between the two answers, as there are two large voters who can form an MWC by themselves in both.

Table 1: Binary choice problems and expected payoffs for Member 1 (subjects)

Problem	Choice A	expected payoff	Choice B	expected payoff
A	$[14; \mathbf{5}, 3, 7, 7]$	$120 * 1/3 * 2/3 = 80/3$	$[14; \mathbf{5}, 4, 6, 7]$	$120 * 1/3 * 3/4 = 30$
B	$[6; \mathbf{1}, 2, 3, 4]$	$120 * 1/3 * 1/3 = 40/3$	$[6; \mathbf{1}, 1, 4, 4]$	$120 * 1/3 * 2/3 = 80/3$
C	$[14; \mathbf{3}, 5, 6, 8]$	$120 * 1/3 * 2/3 = 80/3$	$[14; \mathbf{3}, 6, 6, 7]$	$120 * 1/3 * 3/4 = 30$
D	$[9; \mathbf{1}, 3, 5, 6]$	$120 * 1/3 * 1/3 = 40/3$	$[9; \mathbf{1}, 2, 6, 6]$	$120 * 1/3 * 2/3 = 80/3$

Subjects are all assigned to Member 1 whose votes are indicated in boldfaced values.

Note that for all binary choice problems listed in Table 1, the committees that give higher expected payoffs to the subjects are the same, regardless of whether the Deegan-Packel index or other well-known power indices (Shapley and Shubik, 1954; Banzhaf, 1965) are employed.[2] This experiment does not intend to verify whether subjects learn the Deegan-Packel index as a payoff-generating function.

The subjects are faced with one of the following sequences of binary choice problems: $A \to B$, $B \to A$, $C \to D$, or $D \to C$, where the first problem is used in the first 40 rounds, and the second in the subsequent 20 rounds. In each round, there are the choice stage and the feedback stage. In each stage, the information on votes and payoffs are hidden from the subjects; each subject needs to view the information he or she wanted to know, as explained below. The subjects are prohibited from taking any notes during the session in which they participate. The subjects should be limited to people who have never participated in such an experiment previously and do not know any power indices in weighted voting games.

[2]We chose the Deegan-Packel index as a basis of our payoff-generating function, because Montero et al. (2008), Aleskerov et al. (2009), Esposito et al. (2012), Guerci et al. (2014), and Watanabe (2014) reported that the most frequently observed winning coalitions were MWCs in their experiments.

2.2 Information Available by Clicking the Mouse

This experiment is computerized by Ruby cgi. Each session proceeds automatically according to a precoded computer program, and the binary choice problems are provided to the subjects and the answers are chosen by them on their computer screens.

Figure 1 shows the contents (with the quota in Problems A and C) subjects see on their screens at the choice stage. The numbers of votes the committee members have in both Choice 1 and Choice 2 are hidden from the subjects in windows (marked as $v_1, \ldots, v_4$ and $w_1, \ldots, w_4$). Using a computer mouse, each subject needs to bring the cursor to the window which hides the information he or she wants to view and then click on the window to open it for viewing. The window closes when the subject moves the cursor to another window and click on it for viewing another information.

We impose a 30-second limit at the choice stage. If the subject does not choose a committee within 30 seconds, then he or she receives any points in that round and automatically proceeds to the feedback stage. The subjects who choose a committee within the time limit automatically proceed to the feedback stage. The remaining time is indicated at the top-right corner of the screen, and the number of rounds in which the subjects are faced with a choice is presented at the top-left corner. All instructions and information subjects need to read for their choice in each round are also noted on the same screens.

The feedback stage has two parts. Figure 2 shows the contents the subjects can see on their computer screens at feedback stage 1 (after choosing Choice 1 at the choice stage). At feedback stage 1, the numbers of votes and the amounts of payoffs for the committee members are hidden from the subjects in windows (marked as $x_1, \ldots, x_4$ for the vote apportionment in the committee the subject chooses and $p_1, \ldots, p_4$ for the amounts of the payoff vector). Each subject needs to open the window hiding the information he or she wants to know by clicking on it with a computer mouse for viewing the information. The window closes when the subject moves the cursor to another window and click on it.

The time limit is also 30 seconds at feedback stage 1. If the subject does not click on OK button within 30 seconds, then he or she automatically proceeds to feedback stage 2. The subjects who click on the button within the time limit automatically proceed to feedback stage 2. The remaining time is indicated at the top-right corner of the screen.

Round 1 out of 60 remaining time 16

Choose one of two committees. The quota is 14 in both committees.
The committee you chose allocates 120 points among four members.
Click on Choice 1 button or Choice 2 button within 30 seconds.

Choice 1	member	YOU	Player 2	Player 3	Player 4
	votes	V1	V2	V3	V4

Choice 2	member	YOU	Player 2	Player 3	Player 4
	votes	W1	W2	W3	W4

Figure 1: Choice stage.

Round 1 out of 60 remaining time 23

Click on OK button within 30 seconds after seeing the following information.
You chose the following committee.

Choice 1	member	YOU	Player 2	Player 3	Player 4
	votes	X1	X2	X3	X4

The committee decided to allocate 120 points in this time as follows.

member	YOU	Player 2	Player 3	Player 4
Points	p1	p2	p3	p4

OK

Figure 2: Feedback stage 1.

Finally, Figure 3 shows the contents which subjects see on the computer screens at feedback stage 2. We impose a 10-second limit at feedback stage 2. At feedback stage 2, the amount of payoff a subject obtained and the cumulative amount of payoffs the subject has earned up to the round are hidden from him or her in windows (marked as *yyy* for the current payoff and *zzz* for the cumulative amount of payoffs); Each subject needs to open the window which hides the information he or she would like to know by clicking on it with a computer mouse for viewing the information. The window closes when the subject moves the cursor to another window and click on it for viewing other information.

The time limit is 10 seconds at feedback stage 2. If the subject does not click on the OK button within 10 seconds, then he or she automatically proceeds to the next round. The subjects who click on the button within the time limit automatically proceed to the next round. The remaining time is indicated at the top-right corner of the screen.

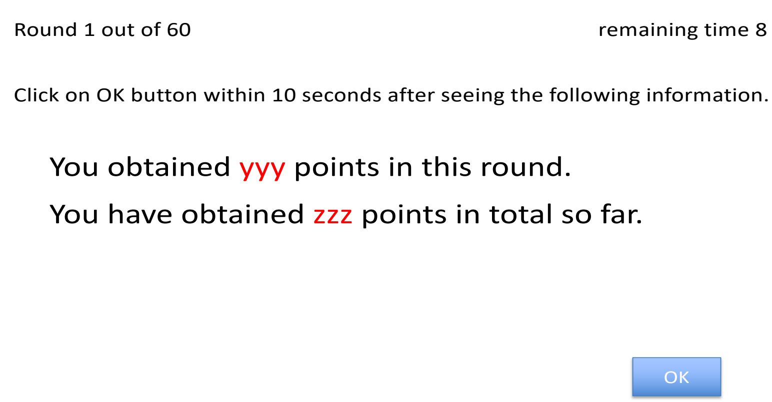

Figure 3: Feedback stage 2.

When subjects answer 60 binary choice problems, the computer screen shows a message that asks them to wait quietly until the others finish. A session ends when all subjects answer 60 binary choice problems. The points earned by the subjects throughout the 60 rounds are then converted into 1 JPY per point and added to the payment for participation. The instructions are provided in the Appendix.

3 Analysis

3.1 Session Details and Overview of the Data

The experiment was conducted from December 17 in 2014 to January 17 in 2017 at the University of Tsukuba. The subjects were undergraduate students recruited from all over the campus. No subject had previously participated in any experimental sessions conducted for Guerci et al. (2017), and no subject participated twice. According to the syllabi of the experimental site, there were no classes in which subjects could learn power indices in weighted voting. In each sequence of binary choice problem, 40 subjects participated in each sequence of binary choice problems, and thus in total 160 subjects participated in the experiment. For the payment scheme, we followed other bandit experiments (Meyer and Shi, 1995; Hu et al., 2013). In the instructions, each subject was informed that in addition to the show-up fee of JPY 1000, he or she would receive payment based on the total amount of points he or she obtained over all 60 rounds at a rate of 1 point = JPY 1. The average earning of our subjects was JPY 2507 (about 18 USD in 2014).

Each session lasted around 60 minutes including the time for administering the instructions and the post-experiment short questionnaire. At the beginning of each session, the subjects were provided with written instructions upon arrival, and then the experimenter read it aloud. No communication among subjects was allowed during each session. Subjects were allowed to ask questions regarding the instruction and they were given the answers privately. Thereafter, any information available to the subjects was provided through their computer screens, which are shown in Figures 1 to 3.

We hereafter say that the subjects chose a correct answer if the answer generated higher expected payoffs. Figure 4 presents the time-series plots of fractions of subjects who chose the correct answer among those who made choices before the time limit in each round for each of the four sequences of binary choice problems. The fractions of those who failed to make their choices before the time limit among subjects are also presented in the same figure. In this section, we first deal with the aggregated data for detecting subjects' meaningful learning according to the definition made by Guerci et al. (2017), and then we analyze the mouse-tracked individual data for finding what each subject actually viewed. We employ a 5% significance level for rejecting the null hypotheses in the statistical analyses.

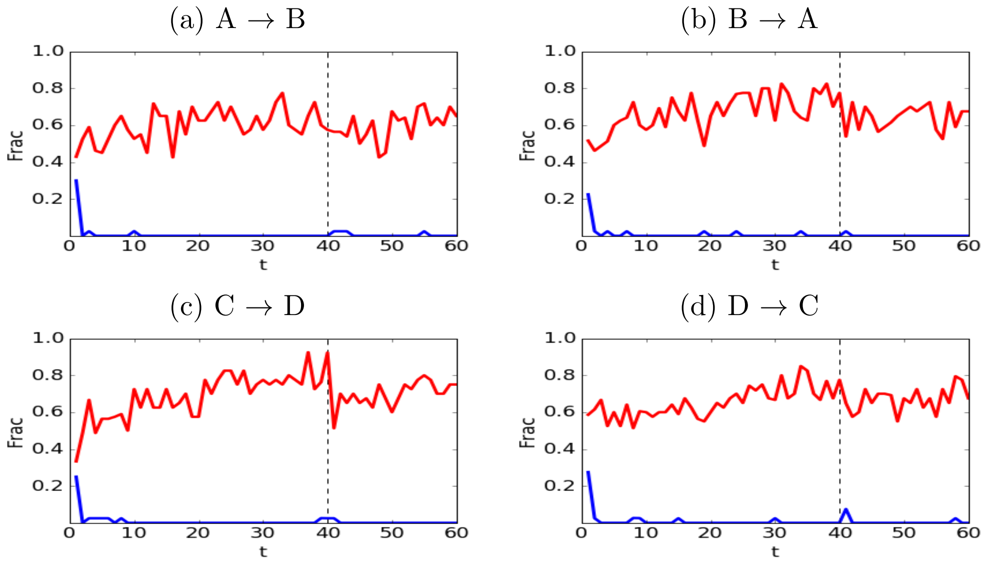

Figure 4: RED: fraction of subjects who chose the correct answer among those who made choices before the time limit in each round for each sequence of the binary choice problems. BLUE: fraction of those who failed to make their choice before the time limit among all subjects. The sample size was 40 for each sequence of binary choice problems. The horizontal lines indicate rounds (t) and the vertical lines indicate the fractions (Frac).

3.2 Aggregate Data: Basic Observations

Let FR_k^i denote the relative frequency of rounds in which subject i chose the correct answer within the k-th block of 5 consecutive rounds, that is, from $5(k-1)+1$ to $5k$. For example, FR_2^i is the number of times subject i chose the correct answer from round 6 to round 10, divided by 5. The change in the relative frequencies that subject i chose the correct answer between the l-th block and the m-th block is defined as

$$\Delta\mathrm{FR}_{l,m}^i = \mathrm{FR}_l^i - \mathrm{FR}_m^i,$$

where $l > m$. Let $\Delta\mathrm{FR}_{l,m}$ (FR_l) denote a vector the i-th component of which is $\Delta\mathrm{FR}_{l,m}^i$ (FR_l^i). In the following analysis, when the elements of FR_l are, on average, significantly larger than those of FR_m, we write this as $\Delta\mathrm{FR}_{l,m} > 0$. When $\Delta\mathrm{FR}_{9,1}$ is referred to in Definition 1, which is described below, FR_9 are the data taken from the "experienced" subjects and FR_1 are the data taken from the "inexperienced" subjects.

	Problem A	Problem B	Problem C	Problem D
$\Delta\mathrm{FR}_{2,1}$	0.0415	**0.0086**	**0.0396**	0.6943
$\Delta\mathrm{FR}_{8,1}$	**0.0143**	<**0.0001**	<**0.0001**	<**0.0001**
$\Delta\mathrm{FR}_{9,1}$	**0.0147**	0.2498	<**0.0001**	**0.0230**

Table 2: P-values for the two-sided signed-rank test (normalized). The rejection of the null hypothesis at the 5% significance level is indicated in boldfaced value

Definition 1 *For each binary choice problem, we consider that subjects learned the "correct" answers if* $\Delta\mathrm{FR}_{8,1} > 0$ *was statistically confirmed and that those who learned in the binary choice problem meaningfully learned the "underlying structure" of weighted voting games if* $\Delta\mathrm{FR}_{9,1} > 0$ *in the same binary choice problem was statistically confirmed.*

These definitions were defined in Guerci et al. (2017). For each binary choice problem, the p-values for the two-sided signed-rank test are reported in Tables 2, where the null hypotheses are $\Delta\mathrm{FR}_{2,1} = 0$, $\Delta\mathrm{FR}_{8,1} = 0$, and $\Delta\mathrm{FR}_{9,1} = 0$, respectively. In this subsection, we used the Bellcurve for Excel 2.03 to process the data. We have the following results.

Result 1 *For all binary choice problems, the subjects learned the correct answer.*

Result 2 *For all binary choice problems except Problem B, the subjects meaningfully learned the underlying structure of weighted voting.*

In a treatment where payoffs for all members in the committee subjects chose were fully fed back, Guerci et al. (2017) could not observe subjects' learning in Problems A and D, and they could not observe meaningful learning by subjects in all binary choice problems. Ogawa et al. (2021) reconfirmed a similar result at four different experimental sites. These papers suggested that withholding immediate payoff-related feedback information should promote subjects' deep inference on the underlying structure of weighted voting. In this experiment, however, subjects learned in all binary choice problems (Result 1) and meaningfully learned in all sequences of binary choice problems except one (Result 2), when they were informed of their own cumulative payoffs. This striking difference provokes a question on which information did subjects who failed in meaningful learning view more frequently or in a longer time on the screens for their choice in this experiment. The analysis conducted in the next subsection gives the answer to this question.

variable	
A_count:	numbers of views of A; $A = v_r, w_r, x_r, p_r$ $(r = 1, 2, 3, 4)$, yyy, zzz
A_time:	cumulative time for viewing A
decision_time:	time spent for the final decision in the choice stage
A_decision_time:	relative length of time spent for viewing A up to the final decision
main2_ok:	time spent in feedback stage 1
main3_ok:	time spent in feedback stage 2
no_info:	dummy variable that takes a value of 1 if the individual subject views $v_1, \ldots, v_4$ or $w_1, \ldots, w_4$ even once; otherwise, 0
judgment:	dummy variable that takes a value of 1 if $\Delta \mathrm{FR}^i_{8,1} > 0$; otherwise, 0
judgment2:	dummy variable that takes a value of 1 if $\Delta \mathrm{FR}^i_{9,1} > 0$; otherwise, 0

Table 3: Major variables.

3.3 Individual Data: Information Viewed Intentionally

Result 2 shows that for all binary choice problems except Problem B, the subjects could meaningfully learn the underlying structure of weighted voting at the aggregate level of data. Then, what are the important factors that subjects saw on the computer screens for their choice? In this subsection, we classify individual subjects into two groups according to whether $\Delta \mathrm{FR}^i_{9,1} = \mathrm{FR}^i_9 - \mathrm{FR}^i_1 > 0$ is satisfied and apply canonical discriminant analysis to the data of variables generated from what the subjects saw on their screens in the first 40 rounds to identify important variables that had a large effect on the classification of the two groups. The major variables are listed in Table 3.

We used SPSS 24.0 for the analysis. A relatively high correlation was found between the numbers of views of $v_1, \ldots, v_4$, $w_1, \ldots, w_4$, and $p_1, \ldots, p_4$ (about 0.6 for any pairs of those variables), and thus the numbers of views of those information were not included as independent variables to avoid multicollinearity. The stepwise method embedded in SPSS was used for our variable selection, and the Mahalanobis distance was applied to the selected variables to identify the discriminant function, because the null hypotheses on the homogeneity of variance-covariance matrices were rejected for almost all sequences of binary choice problems in the Box's M test. The standardized coefficients in the canonical discriminant functions allowed us to compare variables measured on different scales; the coefficients with greater absolute values corresponded to variables with greater discriminating ability.

Preliminaries

At the individual level of data, subjects' learning and meaningful learning are defined in the same binary choice problems in different sequences. The average rates of correct answers within the first 5 consecutive rounds (the average values of elements of FR_1) were 0.455, 0.485, 0.475, and 0.525 in Problems A, B, C, and D, respectively. The p-value for the Brunner-Munzel test was 0.570 (0.380), where the null hypothesis was that the elements of FR_1 are, on average, the same between Problems A and B (C and D). Thus, there was no significant difference in the difficulty to choose the correct answer between two binary choice problems in each sequence of those. We therefore define meaningful learning at the individual level of data as follows.

Definition 2 *For each sequence of binary choice problems, we considered that subject i learned the "correct" answers if $\Delta\mathrm{FR}^i_{8,1} > 0$ in the binary choice problem and that those who learned in the binary choice problem meaningfully learned the "underlying structure" of weighted voting games if $\Delta\mathrm{FR}^i_{9,1} > 0$ in a different but similar binary choice problem.*

In the sequence of A→B, B→A, C→D, and D→C, the numbers of subjects who succeeded in learning (meaningful learning) were 20, 30, 32, and 28 (14, 13, 19, 18), respectively, under Definition 2. Let $G^{81}_1(s)$ denote the group of individual subjects who learned the correct answer in Problem s $(= A, B, C, D)$. Namely, for each member $i \in G^{81}_1(s)$, we have $\Delta\mathrm{FR}^i_{8,1} > 0$ in Problem s. Denote the group of the others by $G^{81}_0(s)$.

In the discriminant analysis, the dependent variable is a dummy variable *judgment2* that takes a value of 1 if $\Delta\mathrm{FR}^i_{9,1} > 0$ (otherwise, 0) and the independent variables are a dummy variable *judgment* that takes a value of 1 if $\Delta\mathrm{FR}^i_{8,1} > 0$ (otherwise, 0) and others which include the major variables listed in Table 3. In the discriminant function for every Problem s $(= A, B, C, D)$, Wilks' lambda for those data was calculated with the p-value being less than 0.001, and thus we could reject the null hypothesis that there was no difference between $G^{81}_0(s)$ and $G^{81}_1(s)$; 68.3%, 61.6%, 78.0%, and 63.1% of the cases were correctly classified for Problems A, B, C, and D, respectively.

What Information Hinders Individual Meaningful Learning?

Let $G_1^{91}(s)$ denote the group of subjects with $\Delta\mathrm{FR}_{9,1}^i > 0$ in Problem s $(= A, B, C, D)$. Denote the group of the others by $G_0^{91}(s)$. $G_1^{91}(s)$ contains subjects with $\Delta\mathrm{FR}_{8,1}^i \leq 0$, and thus, we should say that it is the group of subjects who might meaningfully learn the underlying structure of weighted voting, although subjects who belong to $G_0^{91}(s)$ failed in meaningful learning. In the following discriminant analysis, however, we have a clear result with this classification of subjects.

We derived discriminant functions in which the dependent variable was *judgment2* and the independent variables were the major variables listed in Table 3. In the discriminant function for every binary choice problem, Wilks' lambda for those data was calculated with the p-value being less than 0.001, and thus we could reject the null hypothesis that there was no difference between $G_0^{91}(s)$ and $G_1^{91}(s)$ for independent variables; 65.4%, 67.9%, 63.0%, and 88.9% of the cases were correctly classified for Problems A, B, C, and D, respectively.

Table 4 shows the standardized coefficients with the four largest absolute values observed in the first 40 rounds in the canonical discriminant functions that separated well $G_0^{91}(s)$ and $G_1^{91}(s)$. It is natural that subjects viewed their vote apportionments (v_i and w_i, $i = 1, \ldots, 4$) and their own points p_1; otherwise, they could neither choose their answers nor infer anything from the results of their choice. We thus pay attention to the numbers of views of their own current payoffs (*yyy*) and cumulative payoffs (*zzz*), and the cumulative time for viewing those variables. In the table, we list *yyy_count* instead of variables with the fifth largest absolute values in Problems B and D.

As shown in Table 4, in Problems B and D, the absolute values on *yyy_count* are shown for reference in the table, although they were not the fifth largest coefficients. Regarding the standardized coefficients of *zzz_count* and *yy_count*, in Problems A, B, and D, the coefficients of *zzz_count* are positive and larger than those of *yy_count*, and thus, it is inferred that subjects who succeeded in meaningful learning viewed the cumulative payoffs more frequently than the current payoffs. Note that in Problems A and D, the coefficients of *yy_count* are negative and large. In Problem C, the coefficients of *zzz_count* and *yy_count* are not listed in the table because of the small absolute values, but the coefficient of *yy_time* takes a negative and large value. These observations are summarized as follows.

Problem A	*zzz_count*	*p1_time*	*v4decision_time*	*yyy_count*	*p3_time*
	0.678	0.627	-0.486	-0.484	-0.378

Problem B	*decision_time*	*x1_decision_time*	*x1_count*	*zzz_count*	*yyy_count*
	-0.827	-0.552	0.521	0.506	0.241

Problem C	*x1_count*	*x3_count*	*yyy_time*	*w4_time*	*v3_time*
	-1.359	1.040	-0.549	0.543	0.473

Problem D	*p4_time*	*zzz_count*	*p1_time*	*no_info*	*yyy_count*
	0.749	0.479	0.315	-0.298	-0.142

Table 4: Standardized coefficients in the canonical discriminant functions: the four largest absolute values observed in the first 40 rounds in the discriminant function that separated well $G_0^{91}(s)$ and $G_1^{91}(s)$ for binary choice problem $s = A, B, C, D$. For Problems B and D, the absolute values on *yyy_count* are shown for reference in the table, although they were not the fifth largest coefficients.

Result 3 *The information on subjects' cumulative payoffs might promote meaningful learning, whereas the information on their own current payoffs did not, or even hindered it.*

The experimental results shown in Guerci et al. (2017) and Ogawa et al. (2021) imply that immediate feedback information might have confused subjects' inference regarding the relationship between nominal voting weights and actual payoffs and prevented them from deeply understanding the underlying structure of weighted voting. In fact, Watanabe (2022) reexamined the data taken for Guerci et al. (2017) and found the evidence for subjects' confusion and behavior (discussed at the end of Section 4).

Result 3 shows that there were some cases in which the immediate feedback information on their own current payoffs hindered subjects from meaningful learning, which is consistent with the previous results mentioned in the last paragraph. When subjects repeatedly viewed the feedback information for their own cumulative payoffs, they might more easily infer which answer was correct.

Then, how did subjects who failed in meaningful learning search for the correct answers, paying more attention to the current payoffs than the cumulative payoffs? Without locating any typical search behavior subjects actually took on, we might not say that we have found a factor that hindered subjects from meaningful learning. Let us proceed to this question. We here pick up two types of search behavior reported in Watanabe (2022).

Search Behavior Taken on and Information Viewed by the Subjects

In this experiment, subjects (member 1) receive 0 or 40 points in any binary choice problems. We say that a subject engages in the win-stay-lose-shift (WSLS) strategy when he or she continues to choose the same answer immediately after obtaining 40 points, while he or she changes answers immediately after obtaining 0 point (Nowak and Sigmund, 1993). At the aggregate level of data, Watanabe (2022) inferred that the subjects who engaged in the WSLS strategy would fail to meaningfully understand the payoff structure behind the weighed voting and showed that it was partly true by reviewing some blocks of 5 consecutive rounds in the data taken for Guerci et al. (2017). We here connect subjects' search behavior to their gaze that characterized in Result 3 at the individual level of data. The individual data of 5 consecutive rounds were, however, too small for the statistical test. We thus conducted the two-sided Fisher test and examined the null hypotheses in every 20 rounds.

For each individual subject i, let a_i denote the number of rounds in which *yyy_count* $-$ *zzz_count* is non-negative and let b_i denote the number of rounds in which *yyy_time* $-$ *zzz_time* is non-negative. We say that in 20 consecutive rounds, subject i paid more attention to the current payoffs (than to the cumulative payoffs), if either $a_i \geq 5$ or $b_i > a_i$ in those rounds. It was easily inferred and actually observed that $b_i \geq a_i$, when $a_i \geq 0$. We applied a stronger criterion when $a_i < 5$. Define *current payoff/WSLS* as the number of subjects who paid more attention to the current payoff among those who took the WSLS strategy and *meaningful/WSLS* as the number of subjects who succeeded in meaningful learning among those who took the WSLS strategy.

Table 5 shows *current payoff/WSLS* and *meaningful/WSLS*.[3] The values in the parentheses are the numbers of subjects who did not pay more attention to the current payoff among those who took the WSLS strategy and the numbers who failed in meaningful learning among those who took the WSLS strategy. The rejection of the null hypothesis in the one-sided binomial test is indicated in boldfaced value. The null hypothesis was that there is no difference in number of subjects between those who paid more attention to the current payoff (meaningfully learned) and those who did not among subjects who took the WSLS strategy. According to the statistical analysis, we have the following result.

[3] There was no subjects who took the WSLS strategy in all 20 consecutive rounds, but it was typically observed that the WSLS strategy was clearly taken in about 10 consecutive rounds out of 20 rounds.

		current payoff/WSLS			meaningful/WSLS		
	rounds	1-20	21-40	41-60	1-20	21-40	41-60
sequence	A $\to$ B	4 (3)	5 (3)	**6 (1)**	4 (4)	5 (3)	4 (2)
	B $\to$ A	5 (1)	3 (0)	2 (1)	2 (4)	2 (1)	2 (1)
	C $\to$ D	**7 (0)**	4 (3)	1 (4)	2 (5)	2 (5)	1 (4)
	D $\to$ C	**5 (0)**	**6 (0)**	**7 (0)**	**0 (5)**	**0 (6)**	2 (5)

Table 5: Frequencies of observations: current payoff, meaningful learning, and WSLS. The rejection of the null hypothesis at the 5% significance level in the one-sided binomial test is indicated in boldfaced value.

Result 4 *For Problem D in the sequence of binary choice problems D and C, subjects who took the WSLS strategy paid more attention to the current payoffs than to the cumulative payoffs and they failed in meaningful learning.*

Next, we consider subjects' random choice of runs of options (Choices 1 and 2). Define *current payoff/runs* as the number of subjects who paid more attention to the current payoff among those who chose the runs randomly and *meaningful/runs* as the number of subjects who succeeded in meaningful learning among those who chose the runs randomly. Under the null hypothesis in the (Wald-Wolfowitz) runs test, the number of runs of options chosen by a subject is a random variable. Note that even if the sequence of options is generated by such a clear choice rule as the WSLS strategy, the null hypothesis is sometimes not rejected in the runs test, since the payoffs associated with options are stochastically determined.[4]

Table 6 shows *current payoff/runs* and *meaningful/runs*. The values in the parentheses are the numbers of subjects who did not pay more attention to the current payoff among those who chose the runs of options randomly and the numbers who failed in meaningful learning among those who chose the runs randomly. The rejection of the null hypothesis in the one-sided binomial test is indicated in boldfaced value. The null hypothesis was that there is no difference in number of subjects between those who paid more attention to the current payoff (meaningfully learned) and those who did not among subjects who chose the runs randomly. For Problem D in the sequence of binary choice problems D and C, the null hypothesis was not rejected in the first 20 rounds, but it was rejected in the subsequent 20 rounds. The latter 20 rounds are more important due to the definition of learning (Definition 2). Thus, we have the following result.

[4]For each round in which a subject did not make any choice, we gave the value of 0 (Choice 1), since the runs test requires the value 0 (Choice 1) or 1 (Choice 2). In the case of all Choice 1 or all Choice 2 observed in 20 consecutive rounds, we rejected the null hypothesis since the subject chose the option deterministically.

Result 5 *For Problem D in the sequence of binary choice problems D and C, subjects who chose the runs of options randomly paid more attention to the current payoffs than to the cumulative payoffs and they failed in meaningful learning.*

		current payoff/runs			meaningful/runs		
	rounds	1-20	21-40	41-60	1-20	21-40	41-60
sequence	A → B	**21 (7)**	13 (10)	15 (10)	9 (14)	8 (16)	**7 (16)**
	B → A	**25 (4)**	17 (9)	**16 (6)**	13 (17)	14 (14)	**8 (15)**
	C → D	**19 (1)**	**16 (4)**	**17 (5)**	10 (10)	9 (10)	12 (11)
	D → C	**30 (0)**	**26 (2)**	**15 (2)**	11 (20)	**9 (20)**	**6 (18)**

Table 6: Frequencies of observations: current payoff, meaningful learning, and random choice of runs. The rejection of the null hypothesis at the 5% significance level in the one-sided binomial test is indicated in boldfaced value.

As far as Problem D was concerned, it was confirmed that the subjects who took the WSLS strategy paid more attention to the current payoffs and that those subjects failed in meaningful learning (Result 4). We had similar findings in the case where the subjects chose the runs of options randomly (Result 5). No clear results were, however, obtained for other binary choice problems than Problem D.

In summary, when subjects took on these types of search behavior, it would be true that immediate feedback information on the current payoffs confused subjects' inference regarding the relationship between nominal voting weights and actual payoffs and prevented them from deeply understanding the underlying structure of weighted voting, although we still had to examine various types of search behavior in other binary choice problems.

4 Final Remarks

One third of the subjects who participated in the sessions conducted for Guerci et al. (2017) were recruited also at the University of Tsukuba, and the other part was conducted at Osaka University. At both experimental sites, as noted repeatedly, Guerci et al. (2017) could not observe meaningful learning in a situation where the subjects were provided with immediate feedback information about their current payoffs but were not provided with their cumulative payoffs until the end of the session. In this mouse-tracking experiment, we observed meaningful learning in a situation where the subjects could view their cumulative payoffs as well as their current payoffs at the end of each round (Result 2). Therefore, it would be inferred that showing the cumulative payoffs to subjects might be an important factor that generated remarkably different results between those experiments.

Another factor that might induce subjects to choose their answers differently is, however, whether they view information shown on their computer screens intentionally. Even if feedback information was provided, it would not be a significant impact on the subjects' choice of the correct answers, unless they carefully viewed and recognized it. Intentional visual recognition of feedback information might enhance the subject's awareness of the information. For a better understanding of the different results noted above, we should conduct an additional experiment where subjects' cumulative payoffs are shown on the screen at the end of each round. This is a possible direction left for future research.

This experiment was conducted at the same experimental site for Guerci et al. (2017) in order to ensure subjects' homogeneity in terms of their characteristics. Note, however, that we cannot compare our results with those reported in Guerci et al. (2017) directly, because cumulative payoffs were not shown on subjects' monitors and mouse trackers were not used in the experimental sessions for Guerci et al. (2017).

For examining the external validity of the results shown in Guerci et al. (2017), Ogawa et al. (2021) conducted the same experiment at four experimental sites that had different characteristics as subject pools in Japan. They reported that meaningful learning of the underlying structure of weighted voting was observed at experimental sites where subjects had, on average, relatively higher ability for pattern recognition of their payoffs. The ability of each subject for his or her visual pattern recognition is measured by the score on the Raven's APM test (Raven score).[5] The external validity of the results reported in this mouse-tracking experiment should be confirmed also with subjects Raven scores, which is a future research.

[5]In each question of the Raven's APM test, eight patterns are drawn, and the subject selects a pattern that matches those visual patterns from the options. The full set of the APM version is composed of 48 questions in total (in Set I and Set II). Guerci et al. (2017), Ogawa et al. (2021), and this experiment used questions 1, 4, 7, and 10 from Set I and questions 1, 4, 7, 10, 13, 16, 19, 22, 25, 28, 31, and 34 from Set II. Subjects were asked to complete in 10 minutes after answering the problems in the bandit experiment. The average Raven score of subjects who participated in this mouse-tracking experiment was 13.0, while the average score of those who participated in the sessions conducted for Guerci et al. (2017) was 12.5. There was, on average, no significant difference in the score between our subjects and those who participated in the sessions for Guerci et al. (2017). Accordingly, we could confirm subjects' homogeneity also in terms of their ability for visual pattern recognition.

Appendix: Instructions

In bandit experiments, the instructions are less informative for subjects, as compared with those in other economic experiments. The instructions for this experiment follow the standard format. The original version was written in Japanese and the text except the explanation for mouseclicking was commonly used in sessions for Guerci et al. (2017).

Instructions

Welcome!

Thank you for participating in this experiment today. You will be paid 1000 JPY for your participation and an additional reward that ranges from 0 to 2400 JPY depending on your choices and performance in the experiment.

First,

- Please follow the instructions of the experimenter.
- Please do not take notes during this session.
- Please remain quiet and especially do not talk with other participants.
- Please do not look at what other participants are doing.
- During the experiment, please maintain an upright posture without leaning on the backrest.
- Do absolutely nothing other than the operation that you are instructed to do.
- Please turn off your mobile phone and definitely refrain from using it.
- If you have any questions or require assistance, please silently raise your hand.

You will be asked to repeatedly make a simple choice between two options. Imagine that you need to represent your interests within a voting committee. This committee decides how to divide 120 points among its members. The committee has three other members, and each member has a predetermined number of votes, which may differ between the members.

The committee will make a decision only when a proposal receives the predetermined required number of votes. You will be told what the required number of votes is. If more than one proposal is put before the committee, the members cannot vote for multiple proposals by dividing their allocated number of votes. A member can vote for only one proposal, and all of his/her votes must be cast for that proposal.

You are asked to choose which of the two possible committees you prefer to join. You will be informed of the number of votes required for a proposal to be approved. **The number of votes allocated to each of the four members of the committee (including you) is hidden by a window. To open a window that hides the number of votes you need to view, hover your cursor over the window and click on it.** The number of votes you have will always be indicated with the label YOU.

There are a total of 60 rounds. In each round, you have 30 seconds to make your choice between the two committees. If you do not make a choice within the 30 seconds in one round, you will receive zero points for that round. When a choice is made, the committee you choose will automatically divide 120 points among the four members. The payoff distributions in the same committee may vary from one round to another, but are based on a theory of decision-making in committees.

You will have an opportunity to view the payoff distribution in the committee immediately. **The payoff distributed to each of the four members of the committee (including you) is hidden by a window. To open a window that hides the payoff you need to view, hover your cursor over the window and click on it.** At the end of the experiment, you will be paid according to your total earnings during the 60 rounds, at an exchange rate of 1 point = 1 JPY. All the other instructions will be presented on your computer screen.

If you have any questions, please raise your hand.

Declarations

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Availability of Data and Material

All raw and processed data are available upon requests.

Code Availability

All data were processed using SPSS 24.0 and Bellcurve for Excel 2.03 (`https://bellcurve.jp/ex/`, in Japanese). The commands used by the author in these softwares are available upon requests.

Ethical Approval

All procedures in this study involving human participants were performed in accordance with the ethical standards of the institutional and/or national research committees and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This article does not contain any studies with animals performed by any of the authors.

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