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Can Subjects Meaningfully Learn Actual Voting Powers?: Pattern Recognition and Feedback Information*

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Abstract

We examined whether subjects generalized (meaningfully learned) what they had learned in a binary choice problem to a similar but different one at each of four experimental sites that had different characteristics as subject pools. Subjects were asked to choose one of two weighted voting games repeatedly and given their payoffs determined by a hidden stochastic payoff-generating function after their choice. Immediate feedback information about payoffs induced subjects to take the win-stay-lose-shift strategy, and thus withholding immediate feedback information promoted subjects' deep inference on the underlying relationship between nominal vote apportionments and their actual payoffs. Meaningful learning was observed at some sites at which subjects' ability for pattern recognition measured by the Raven APM test were relatively higher than those at other sites. Subjects who have experienced easier binary choice problems in early periods meaningfully learn the underlying structure of weighted voting.

Keywords: meaningful learning, weighted voting, pattern recognition, bandit experiment, win-stay-lose-shift strategy

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1 Introduction

Weighted voting is a popular collective decision-making system, which is used not only in multi-party legislatures but also in stockholder voting in corporations and so on. Felsenthal and Machover (1998, pp.164-165), however, noted that it might be difficult even for the policy makers and officials who designed and re-designed the system to see the underlying relationship between the actual voting powers and the nominal voting weights.[1] This paper considers whether subjects can "meaningfully" learn the latent feature of weighted voting in a bandit experiment in the context of weighted voting, conducting the sessions at four experimental sites.

1.1 Background of This Research

When people generalize what they have learned in a situation to a similar but different one, this higher order concept of learning is called meaningful learning (Rick and Weber, 2010).[2] In strategic situations repeatedly played by subjects, feedback information provided to each subject contains the outcomes generated by unplanned or exploratory behavior of other subjects, and thus individual inferences might be confused mutually among subjects. In order to investigate individual meaningful learning about the underlying structure of weighted voting, Guerci et al. (2017) drastically simplified the experimental design to remove subjects' learning through their strategic interaction. We followed their experimental design, which is is as follows. In each session subjects choose one of two weighted voting games (options) repeatedly and obtain their payoffs which are stochastically generated for each choice they make according to a voting theory. The binary choice problems are different between the first and second parts of the session, but the payoff generating function in binary choice problems remains the same. Subjects thus have a chance to learn something underlying the situation they face in the first part and to apply what they learned in the first part to their decision in the second part.

[1]Gelman et al. (2004) noted that empirical measures of voting powers present considerably different outcomes from the prediction that the theoretical measures developed by Shapley and Shubik (1954) and Banzhaf (1965) suggest. This gap is an example that shows the underlying structure of weighted voting is remarkably complex, although the rule is relatively simple.

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

In that experiment, Guerci et al. (2017) could not observe meaningful learning by subjects when immediate payoff-related feedback information was provided them, but they observed it only in sessions without any feedback information. Feedback information is, however, essential in the standard theories such as reinforcement learning (e.g., Erev and Roth, 1998), belief-based learning (e.g., Cheung and Friedman, 1997), and experience weighted attraction learning (Camerer and Ho, 1999). Was the observation by Guerci et al. (2017) an outcome of chance or a consequence of subjects' extraordinary choice at particular experimental sites?

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) so that they were confused with immediate payoff-related feedback information. Without feedback information, subjects cannot execute the WSLS strategy. Also, subjects' ability for recognizing the pattern of their payoffs might have an important relationship with their meaningful learning of the latent feature of weighted voting.

1.2 Outline and Results

In this experiment, each subject was asked to choose one of two weighted voting games many times, and his or her payoff was stochastically determined for each choice according to a theoretical index of voting power. The payoff-generating function remained intact but hidden from subjects throughout the session. Each session had 40 periods for the first binary choice problem and 20 periods for the second one. Subjects' ability for pattern recognition was measured by the Raven's test (Raven scores). For testing the following hypotheses, the sessions were conducted at four universities in Japan so that the Raven scores of subjects are, on average, significantly different among some of those universities.

Hypothesis 1 *Immediate payoff-related feedback information induces subjects to take the win-stay-lose-shift strategy that might hinder them from meaningfully learning the latent feature of weighted voting.*

Hypothesis 2 *Meaningful learning of the underlying structure of weighted voting is observed at experimental sites where subjects have, on average, relatively higher ability for pattern recognition of their payoffs.*

We provide one more hypothesis on the difficulty of binary choice problems, according to a fact extracted from outcomes in Guerci et al. (2017). As noted at the beginning of this section, weighted voting is a popular collective decision-making system. Accordingly, we should consider an environment in which people can deeply infer the underlying structure of weighted voting. We say that a binary choice problem is an easy one if one option has two voters who can form a winning coalition by themselves while the other does not have those "large" voters. If there is no such a clear difference between the two options, we say that the binary choice problem is difficult to find the correct answer.

Hypothesis 3 *Subjects who have experienced easy binary choice problems in early periods meaningfully learn the underlying structure of weighted voting, but they fail to meaningfully learn it when they have experienced difficult binary choice problems in the early periods.*

Our observations are as follows. (1) Immediate feedback information about subjects' payoffs induced them to take the win-stay-lose-shift strategy; feedback information might confuse their inference on the relationship between nominal voting weights and actual payoffs and prevented them from deeply understanding the underlying structure of wighted voting. (2) When the immediate payoff-related feedback information was withheld, however, we observed meaningful learning at experimental sites where subjects' average Raven scores were significantly higher than do subjects at other sites. There could be an affirmative relationship between subjects' ability for recognizing the pattern of payoffs and their ability for generalizing their knowledge they obtained from their experiences to a similar but different situation. (3) We reconfirmed that meaningful learning was observed only in a difficult binary choice problem which subjects were faced with after their experience with an easy binary choice problem, checking a search behavior of each subject.

The remainder of the paper is organized as follows. Section 2 describes the experimental design. We first describe the baseline of the experiment, next display what subjects see on their monitors, and lastly note the Raven test we use. Section 3 mentions the session details and Section 4 derives the experimental results. Section 5 concludes this paper and discusses some topics on future research. Appendix A displays the time series plots of the rates of correct answers subjects chose for each treatment at each experimental site. Appendix B shows the results for detecting the win-stay-lose shift strategy in the last 20 periods.

2 Experimental Design

2.1 Binary Choice Problem

Each session consists of 60 periods. In each period, subjects are asked to choose one of two four-member committees (weighted voting games) that will divide 120 points among the members, and they are given payoffs which are stochastically determined by a payoff-generating function that is hidden from subjects throughout the session. This type of experiments is called a two-armed bandit experiment with the contextual information.

Let $N = \{1, 2, 3, 4\}$ be the set of the members (players) of a committee (voting game). A committee is represented by $[q; v_1, v_2, v_3, v_4]$, where v_i is the number of votes (voting weight) allocated to member $i \in N$ and q is the minimum number of votes required for an allocation to be adopted (quota). Every subject acts as Member 1. The subjects face one binary choice problem, e.g., a choice between $[14; 5, 3, 7, 7]$ and $[14; 5, 4, 6, 7]$ for the first 40 periods, and in the following 20 periods they face a similar but different binary choice problem, e.g., a choice between $[6; 1, 2, 3, 4]$ and $[6; 1, 1, 4, 4]$. As shown in those examples, the two committees in question have the same total number of votes, the same quota, and the same number of votes for the subject. The subjects are informed that the other committee members are all fictitious, they do not play the weighted voting games they choose, and their payoffs are stochastically determined for their choice based on a voting theory.

The payoff each subject obtains from his or her choice is determined by the Deegan-Packel index (DPI) developed by Deegan and Packel (1978). Given a weighted voting game, a non-empty subset S of N is called a coalition, and a coalition is called a winning coalition if $\sum_{i \in S} v_i \geq q$; otherwise, it is called a losing coalition. 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, for each period, one MWC is drawn with equal probability from all possible MWCs for the committee that the subject chooses. If the subject is a member of the MWC drawn at random, then he or she receives an equal share of the total payoff with the other members; otherwise, he or she receives nothing.

The example of the DPI is as follows. Denote each MWC by the votes apportioned to its members; e.g., there are three MWCs in a weighted voting game $[14; 5, 3, 7, 7]$, and they are written as $(5, 3, 7)$, $(5, 3, 7)$, and $(7, 7)$. Member 1 belongs to two MWCs out of three, i.e., $(5, 3, 7)$ and $(5, 3, 7)$, each having three members. The DPI of Member 1 is thus $2/3 \times 1/3 = 2/9$ and the expected payoff for Member 1 is $120 \times 2/3 \times 1/3$. The binary choice problems we use are shown in Table 1.[3] As shown in the table, the committee that generates a higher expected payoff for subjects (correct answer) is Choice 2 for all problems. This experiment does not intend to verify whether subjects learn the DPI as a payoff-generating function; we use binary choice problems in which the better committees for the subjects are the same regardless of whether we employ DPI or other voting power indices such as the Banzhaf index (Banzhaf, 1965) and the Shapley-Shubik index (Shapley and Shubik, 1954).[4]

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

Problem	Choice 1	(expected payoff)	Choice 2	(expected payoff)
A	$[14; \mathbf{5}, 3, 7, 7]$	$(120 \times 2/3 \times 1/3)$	$[14; \mathbf{5}, 4, 6, 7]$	$(120 \times 3/4 \times 1/3)$
B	$[6; \mathbf{1}, 2, 3, 4]$	$(120 \times 1/3 \times 1/3)$	$[6; \mathbf{1}, 1, 4, 4]$	$(120 \times 2/3 \times 1/3)$
C	$[14; \mathbf{3}, 5, 6, 8]$	$(120 \times 2/3 \times 1/3)$	$[14; \mathbf{3}, 6, 6, 7]$	$(120 \times 3/4 \times 1/3)$
D	$[9; \mathbf{1}, 3, 5, 6]$	$(120 \times 1/3 \times 1/3)$	$[9; \mathbf{1}, 2, 6, 6]$	$(120 \times 2/3 \times 1/3)$

Note: Subjects are all assigned to Member 1 in each committee. The numbers of votes for Member 1 are indicated as boldfaced values. The correct answer is Choice 2 in every binary choice problem. The MWCs and payoff distributions are listed in Table 2.

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 periods, and the second one in the subsequent 20 periods (the order is indicated by the arrow). See Table 2 for the payoff vector for each choice. For any choice, subjects obtain 40 points, if a MWC to which Member 1 belongs is selected; otherwise nothing. Subjects are not informed of what binary choice problems being given before those problems are shown on their monitors.

This experiment has three treatments: (1) no feedback, (2) partial feedback, and (3) full feedback. For the no-feedback treatment, subjects are not informed of any payoffs of any members in the committee they chose. For the partial-feedback treatment, each subject is informed of his or her own payoff in the committee he or she chose. For the full-feedback treatment, subjects are informed of the payoffs of all four members in the committee they chose. Subjects are prohibited from taking notes.

[3] Those problems were used also in Guerci et al. (2014), Guerci et al. (2017), and Watanabe (2018).

[4] 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.

Table 2: MWCs and payoff vectors.

Problem A	Choice 1	[14; 5, 3, 7, 7]	Choice 2	[14; 5, 4, 6, 7]
	$(7_1, 7_2)$	(0, 0, 60, 60)	(5, 4, 6)	(40, 40, 40, 0)
	$(5, 3, 7_1)$	(40, 40, 40, 0)	(5, 4, 7)	(40, 40, 0, 40)
	$(5, 3, 7_2)$	(40, 40, 0, 40)	(5, 6, 7)	(40, 0, 40, 40)
			(4, 6, 7)	(0, 40, 40, 40)
Problem B	Choice 1	[6; 1, 2, 3, 4]	Choice 2	[6; 1, 1, 4, 4]
	(2, 4)	(0, 60, 0, 60)	$(4_1, 4_2)$	(0, 0, 60, 60)
	(3, 4)	(0, 0, 60, 60)	$(1_1, 1_2, 4_1)$	(40, 40, 40, 0)
	(1, 2, 3)	(40 40, 40, 0)	$(1_1, 1_2, 4_2)$	(40, 40, 0, 40)
Problem C	Choice 1	[14; 3, 5, 6, 8]	Choice 2	[14; 3, 6, 6, 7]
	(6, 8)	(0, 0, 60, 60)	$(6_1, 6_2)$	(40, 40, 40, 0)
	(3, 5, 6)	(40, 40, 40, 0)	$(1, 2, 6_1)$	(40, 40, 0, 40)
	(3, 5, 8)	(40, 40, 0, 40)	$(1, 2, 6_2)$	(40, 0, 40, 40)
			$(6_1, 6_2, 7)$	(0, 40, 40, 40)
Problem D	Choice 1	[9; 1, 3, 5, 6]	Choice 2	[9; 1, 2, 6, 6]
	(3, 6)	(0, 60, 0, 60)	$(6_1, 6_2)$	(0,0, 60, 60)
	(5, 6)	(0, 0, 60, 60)	$(1, 2, 6_1)$	(40, 40, 40, 0)
	(1, 3, 5)	(40, 40, 40, 0)	$(1, 2, 6_2)$	(40, 40, 0, 40)

Note: The MWCs are not denoted by player ID but by the votes apportioned to the members.

We impose a time limit for the choice stage and another time limit for the feedback stage. If a subject does not choose a committee within 30 seconds, then he or she is informed of his or her zero points for that period in the feedback stage. If a subject makes a choice before the time limit, then he or she is asked to wait until all subjects in the session have made their decisions. When all the subjects make their choices, they all enter the feedback stage. For the partial-feedback and full-feedback treatments, the relevant payoff information is displayed during these 10 seconds. For the no-feedback treatment, subjects are asked to wait during the feedback stage, regardless of their choice or no-choice.

This experiment is computerized by using zTree (Fischbacher, 2007). For subjects who complete their choice before the 30-second time limit has elapsed, a message instructing the subject to wait is displayed on the computer monitor. When all subjects participating in the session have completed their choice or the time of 30 seconds in the choice stage has elapsed, the information browsing time of 10 seconds proceeds at once. For the no-feedback treatment, an indication to wait until the next alternative is presented is displayed on the subject's computer monitor as described above.

2.2 Subject's Monitor

The instructions for bandit experiments are never informative, because subjects' learning and its process are investigated under simple situations. We here illustrate what subjects actually see on their monitors in each period. Superscripts such as YOU, Member 2, Member 3, and Member 4 are here omitted for the vote apportionments and the payoff distribution.

Please choose one out of the following two committees (Choice 1 or Choice 2). Each committee decides a distribution of 120 points among four members. You are Member 1. In both committees, 22 votes are apportioned to those members and you have 5 votes. Any proposals of point distributions need 14 votes in favor to be adopted.

$$\text{Choice 1} \quad [14; \mathbf{5}, 3, 7, 7], \quad \text{Choice 2} \quad [14; \mathbf{5}, 4, 6, 7]$$

When subjects choose Choice 2 and MWC $(5, 6, 7)$ appears, they see, for instance, the following results on their monitor, regardless of any treatments.

You chose the following committee.

$$\text{Choice 2: } [14; \mathbf{5}, 4, 6, 7].$$

Next, in the full-feedback treatment, subjects see

The committee decided to distribute 120 points this time as follows.
You obtained 40 points this time.

(**40**, 0, 40, 40)

on their monitors. In the partial-feedback treatment, the payoff distribution is not shown, but rather the following note is shown on their monitors:

You obtained 40 points this time.

In the no-feedback treatment, the payoff distribution is not shown and simply

Please wait for a while.

is shown on the subjects' monitors. (In the instructions, they are announced that their payoffs are not shown until the end of the session.)

2.3 The Raven's Advanced Progressive Matrices Test

The Raven's test is one of the well-known tests that measure subject's ability for visual pattern recognition which would be directly related to the subjects' learning of the correct answer from their pattern recognition of payoffs under vote apportionments. The primary purpose of this experiment examines hypotheses on meaningful learning, but the secondary one is related to Hypothesis 2 and noted as follows: is there any relationship between subjects' ability for recognizing the pattern of payoffs and their ability for generalizing their knowledge they obtained from their experiences to a similar but different situation?

In each question of the test, eight patterns are drawn, and the subject selects a pattern that matches those visual patterns from the options. (See, e.g., Carpenter et al. (1990) and Raven (2000).) There are three versions of the test, Colored Progressive Matrices (CPM), Standard Progressive Matrices (SPM), and Advanced Progressive Matrices (APM), in ascending order of difficulty. We used 16 of 48 questions of the APM version that the subjects were asked to complete after answering all of the problems in the bandit experiment and ask subjects to complete the answers in 10 minutes. In this paper, the Raven score refers to the number of correct answers to the 16 questions on the APM version.[5]

3 Session Details

The sessions were conducted from March 2 in 2018 to October 17 in 2019 at Kansai University (Senriyama campus), Osaka Sangyo University, Doshisha University (Imadegawa campus), and Hiroshima City University so that we could obtain the data from subjects with different Raven scores at different sites.[6] At each site, subjects were undergraduate students recruited from all over the campus, and in syllabi there were no classes in which they could learn voting power indices. Every subject participated only once in this experiment. In total, 816 subjects participated in the experiment, and the average amount paid as a reward was 2534 JPY (1 USD was about 110 JPY).

[5]The APM version has 48 questions (in Set I and Set II), and it takes 30 minutes to complete those 48 questions. We included 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. These 16 questions were also used in the studies by Hanaki et al. (2016), Guerci et al. (2017), Watanabe (2018), Kawamura and Ogawa (2019), and Watanabe et al. (2020). Gill and Prowse (2016) and Basteck and Mantovani (2018) used the SPM version, and Proto et al. (2019) used 30 questions selected from Set II of the APM version. Set II contains 36 questions.

[6]Doshisha University has the faculty of science and engineering, but it is located at another campus.

We have two groups of experimental sites, Group A and Group B. (The difference between those groups is explained in the next paragraph.) At Kansai University, subjects were recruited for both groups but each subject was randomly assigned to only one group; those subjects are referred to as Kansai U-A and Kansai U-B. The subjects who participated in this experiment at Osaka Sangyo University, Doshisha University, and Hiroshima City University are noted as Osaka SU, Doshisha, and Hiroshima CU, respectively.

The same experimenter gave the instructions to the subjects of Group A (Kansai U-A, Osaka SU) and paid a uniform amount of 500 JPY for their participation, regardless of whether the subject correctly answered the questions of the Raven test conducted after their choice in the bandit experiment on weighted voting, whereas the instructions were read out using text-to-speech software to subjects of Group B (Kansai U-B, Doshisha, Hiroshima CU) and a monetary reward of 50 JPY for each correct answer was paid. In both groups, subjects were paid a reward for the points they earned in the sessions.[7]

Tables 3 and 4 list the number of subjects and the average amount of payment (avg. pay) in each session, where decimals are rounded off, and no-feedback, partial-feedback, and full-feedback treatments are abbreviated as No-fb, Part-fb and Full-fb, respectively. Problems A, B, C, and D were examined in Group A, while Problems A and B were examined in Group B because of the limited number of subjects at Hiroshima CU.[8]

Table 3: Numbers of participants in sessions at Kansai U-A and Osaka SU.

	treatment	A→B	B→A	C→D	D→C	# of subj.	avg. pay
Kansai U-A	No-fb	20	20	20	20	80	2480
	Part-fb	20	20	20	20	80	2537
	Full-fb	20	20	20	20	80	2483
	# of subj.	60	60	60	60	240	2495
Osaka SU	No-fb	10	10	10	10	40	2420
	Part-fb	10	10	10	10	40	2506
	Full-fb	10	10	10	10	40	2517
	# of subj.	30	30	30	30	120	2481

[7]This difference in use of text-to-speech software were simply due to the fact that the experimenter of Group A could not attend all the sessions conducted at Doshisha and Hiroshima CU. We could not observe any significant difference in Raven scores between Kansai U-A and Kansai U-B, although the payment schemes for the part of the Raven's test were different.

[8]See Appendix A of Ogawa et al. (2020) for more details.

Table 4: Numbers of participants in sessions at Kansai U-B, Doshisha, and Hiroshima CU.

	treatment	A→B	B→A	# of subj.	avg. pay
Kansai U-B	No-fb	45	27	72	2401
	Part-fb	27	26	53	2571
	Full-fb	29	43	72	2643
	# of subj.	101	96	197	2586
Doshisha	No-fb	27	20	47	2567
	Part-fb	28	20	48	2632
	Full-fb	20	20	40	2543
	# of subj.	75	60	135	2581
Hiroshima CU	No-fb	20	20	40	2424
	Part-fb	23	20	43	2661
	Full-fb	21	20	41	2593
	# of subj.	64	60	124	2519

Table 5 lists the subjects' attributes at each experimental site. The male-to-female ratios were almost even at Kansai U-A and U-B, while the subjects at Osaka SU and Hiroshima CU were overwhelmingly male and female, respectively. The male-to-female ratio of subjects at Osaka SU (Hiroshima CU) is significantly higher (lower) than that of the subjects at Kansai U-A (Kansai U-B), while there was no significant difference in the ratio between Kansai U-B and Doshisha. Doshisha (Imadegawa campus) does not have science and engineering departments (sci-eng) and there are no economics major students (econ) at Hiroshima CU.

Table 5: Subjects' attribute information.

site	# of subj.	male	female	p-value	econ	sci-eng	others
Kansai U-A	240	128	112		21	53	166
Osaka SU	120	99	21	**<0.001**	47	38	35
Kansai U-B	197	98	99		24	41	132
Doshisha	135	76	56	0.828	21	0	114
Hiroshima CU	124	49	75	**0.047**	0	24	100

Note: The p-values for the Fisher exact test for male-to-female ratio were computed in comparison with Kansai University (Kansai U-A and Kansai U-B). The one-sided test was applied to comparison between Kansai U-A and between Kansai U-B and Hiroshima CU, where the null hypothesis is that male-to-female ratio at OSU (Hiroshima CU) was equal to or lower (higher) than that ratio at Kansai U-A (Kansai U-B). The two-sided test was applied to comparison between Kansai U-B and Doshisha, where the null hypothesis is that male-to-female ratios was the same between those experimental site. Emboldened values indicate rejection of the null hypothesis at the 5% significance level.

Table 6 shows the basic statistics for the Raven scores at each experimental site.[9] The table also shows the p-values for Brunner-Munzel test (Brunner and Munzel, 2000). According to the test, we have (1) that subjects at Kansai U-A scored significantly higher on average than those at Osaka SU; (2) that no significant difference existed between subjects at Kansai U-B and those at Doshisha; and (3) that subjects at Kansai U-B scored significantly higher on average than those at Hiroshima CU.

Table 6: Raven scores of subjects: basic statistics.

site	# of subj.	mean	std.dev.	p-value	min	max
Kansai U-A	240	11.208	2.170		3	16
Osaka SU	120	10.625	3.041	**0.027**	3	16
Kansai U-B	197	11.518	2.398		2	15
Doshisha	135	11.578	2.300	0.890	5	16
Hiroshima CU	124	10.976	2.441	**0.038**	3	15

Note: The p-values for the Brunner-Munzel test were computed in comparison to the data taken at Kansai University (Kansai U-A and Kansai U-B). The null hypothesis is that Raven scores of subjects at an experimental site are, on average, the same as those at Kansai University. Emboldened values indicate rejection of the null hypothesis at the 5% significance level.

The Economic Experiment Laboratory at Kansai University had a subject pool of non-student general public living in the northern part of Osaka Prefecture. Table 7 presents basic statistics of their Raven scores and Figure 1 depicts the histogram. The average Raven scores of the college students who participated in this experiment were clearly higher than those of the non-student general public, according to the values shown in Table 6 and Table 7. We refer to this difference at the beginning of Section 5 for the inference of whether people can meaningfully learn the underlying structure of weighted voting.

4 Analysis

We employ a 5% significance level in rejecting the null hypotheses. See the Appendix A for diagrams that present the time series plots of the average rates of correct answers for each period in each of the sequences of binary choice problems at each experimental site.

[9] Those average scores do not represent the ability of representative students for pattern recognition at the experimental sites. Prior to proceeding to the experiment, all subjects agreed to take a cognitive ability test. According to the standard procedure, the experimenter announced that they could withdraw their participation at any time during the session, but no subjects did not withdraw. The Raven scores are disclosed to the subjects who concerned upon their request.

Table 7: Raven scores of non-student general public: basic statistics.

subject pool	# of subj.	mean	std. dev.	min	max
Kansai U	1,015	7.974	3.267	0	16

Note: The Raven scores of non-student general public were measured from April 2015 to Feb 2018. Among 1015 subjects in total, 488 subjects participated in the sessions for Kawamura and Ogawa (2019), the average age of whom was around 55.

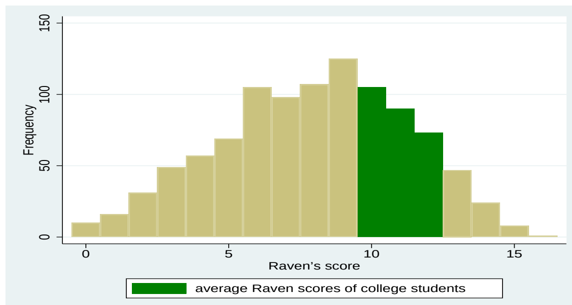

Figure 1: Histogram of the Raven scores of non-student general public. The range of the average raven scores of our subjects is colored in green.

4.1 Learning and WSLS Strategy

As shown in Table 2, 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.

In each session, a few subjects could not choose any options within the time limit when they were faced with binary choice problems they had not experienced. Table 8 lists the percentage of subjects who chose the correct answer in the 1st and 41st period for each treatment at each experimental site; in almost all sessions, the percentages of those subjects for Problem B were lower than the percentages of those subjects for Problem A, and thus it was more difficult for subjects to obtain the correct answer for Problem B than for Problem A. Similarly, Problem D was more difficult than Problem C. In each of Problems A and C, there is a committee in which a winning coalition forms with two voters, while in the alternative committee there is no such a coalition. In Problems B and D, however, both committees have winning coalitions formed by two voters.

Table 8: Percentage of subjects who chose the correct answer in the 1st and 41st periods.

	period 1	No-fb	Part-fb	Full-fb	period 41	No-fb	Part-fb	Full-fb
Kansai U-A	Problem A	0.700	0.700	0.600	Problem A	0.700	0.550	0.550
	Problem B	0.200	0.250	0.200	Problem B	0.400	0.500	0.400
	Problem C	0.700	0.700	0.650	Problem C	0.550	0.700	0.550
	Problem D	0.450	0.550	0.400	Problem D	0.800	0.450	0.450
Osaka SU	Problem A	0.600	0.700	0.300	Problem A	0.400	0.600	0.400
	Problem B	0.400	0.300	0.500	Problem B	0.300	0.300	0.300
	Problem C	0.600	0.600	0.600	Problem C	0.800	0.700	0.700
	Problem D	0.600	0.100	0.200	Problem D	0.200	0.300	0.500
Kansai U-B	Problem A	0.689	0.741	0.621	Problem A	0.778	0.538	0.535
	Problem B	0.333	0.308	0.349	Problem B	0.489	0.370	0.345
Doshisha	Problem A	0.593	0.679	0.800	Problem A	0.700	0.550	0.500
	Problem B	0.400	0.450	0.350	Problem B	0.519	0.464	0.350
Hiroshima CU	Problem A	0.500	0.609	0.714	Problem A	0.600	0.250	0.550
	Problem B	0.350	0.300	0.350	Problem B	0.500	0.478	0.381

Let FR_k^i denote the relative frequency of periods in which subject i chose the correct answer within the k-th block of 5 consecutive periods, 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 period 6 to period 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 $\Delta\mathrm{FR}_{l,m}$ denote a vector whose i-th component is $\Delta\mathrm{FR}_{l,m}^i$.

For Part-fb and Full-fb, however, it is plausible to consider that subjects who engage in the WSLS strategy do not have confidence in their own understanding of the payoff structure behind the weighed voting, which may be considered an evidence that subjects did not learn. For No-fb, the WSLS strategy is not chosen because there is no feedback information. We require instead correct answer rates of 60% or higher to say that subjects learned, because the correct answer rate would be 50% even by random choice. Eventually, we added two conditions for strengthening the definition of subjects' learning made in Guerci et al. (2017).

Definition 1 *For each binary choice problem, we consider that subjects learned the correct answers, if (1)* $\Delta\mathrm{FR}_{8,1} > 0$*, (2) the WSLS strategy is not observed in the 8th block of 5 consecutive periods for the partial-feedback and full-feedback treatments, and (3) the rate of correct answers is at least 60% in the 8th block, regardless of feedback treatments.*

We do not insist that subjects certainly learned the correct answers when condition (3) is met, but we intend to conclude that they did not learned the correct answers if the rate of correct answers is less than 60%; higher values might be discussed. In Full-fb and Part-fb, however, subjects current choice depends on their previous choice they made and randomization made by payoff-generating function, and thus subjects choice cannot be considered as an independent random choice at each opportunity. The run test would be appropriate for testing subjects' random choice of runs of those sequential search behavior. But, the power of the test would be low in the case of only 5 consecutive periods. Accordingly, we set 60% as a threshold value in Definition 1. Again, we conclude that subjects did not learned the correct answers unless condition (3) was satisfied.

For each binary choice problem, the p-value for the one-tailed signed-rank (SR) test for each feedback treatment is reported in Tables 9 and 10, where the null hypothesis is $\Delta\mathrm{FR}_{8,1} \leq 0$ and the alternative hypothesis is $\Delta\mathrm{FR}_{8,1} > 0$. As for Group A, at Kansai U-A, the null hypothesis was rejected for every treatment of feedback information in Problems B and D except the case of Full-fb in Problem D, while at Osaka SU, it was rejected for Part-fb in Problem B. As for Group B, the null hypothesis was rejected in Problem B for each of Part-fb and Full-fb at Kansai U-B, for Part-fb at Doshisha, and for each of No-fb and Full-fb at Hiroshima CU.

Table 9: p-values for one-tailed SR test, $\Delta\mathrm{FR}_{8,1}$, Group A.

	Kansai U-A			Osaka SU		
	No-fb	Part-fb	Full-fb	No-fb	Part-fb	Full-fb
Problem A	0.227	0.387	0.212	0.688	0.125	0.363
Problem B	**0.048***	**0.001***	**0.001**	0.855	**0.008***	0.500
Problem C	0.500	0.212	0.227	0.813	0.500	0.109
Problem D	**0.038***	<**0.001**	0.059	0.227	0.500	0.172

Note: The null hypothesis is that $\Delta\mathrm{FR}_{8,1} \leq 0$. The WSLS strategy in the 8th block was observed in Problem D for Part-fb and in Problem B for Full-fb at Kansai U-A, as shown in Tables 11 and 12. For No-fb at Kansai U-A, the rate of correct answers is 0.60 in Problem B and it is 0.62 in Problem D, as shown in Table 16. The asterisk indicates that learning was observed.

Table 10: p-values for one-tailed SR test, $\Delta\mathrm{FR}_{8,1}$, Group B.

	Kansai U-B			Doshisha			Hiroshima CU		
	No-fb	Part-fb	Full-fb	No-fb	Part-fb	Full-fb	No-fb	Part-fb	Full-fb
Problem A	0.066	0.668	0.115	0.808	0.808	0.151	0.395	0.315	0.105
Problem B	0.402	<**0.001**	**0.007**	0.090	<**0.001**	0.240	**0.011**	0.227	**0.006***

Note: The null hypothesis is $\Delta\mathrm{FR}_{8,1} \leq 0$. The WSLS strategy in the 8th block was observed in Problem B for Part-fb at Kansai U-B and Doshisha and for Full-fb at Kansai U-B, as shown in Tables 13, 14, and 15. For No-fb at Hiroshima CU, the rate of correct answers is 0.58 in the 8th block of 5 consecutive periods, as shown in Table 16. The asterisk indicates that learning was observed.

In detecting the WSLS strategy, we count the number of choice changes in 5 periods. For each binary choice problem for Part-fb and Full-fb at each experimental site, Tables 11-15 present the frequencies (freq) of observing 0 or 40 points, the numbers of observations of changing alternatives (switch), the switching ratios for each frequency of observing 0 or 40 points in 8th block of consecutive 5 periods, and p-values for the two-sided Fisher exact test where the null hypothesis is that switching choices immediately after observing 0 points and switching choices immediately after observing 40 points were equally likely to be observed. Table 16 presents the average rates of correct answer in the 1st and 8th block of consecutive 5 periods in each binary choice problem for each treatment.

In Group A, consider the cases of Problems B and D. At Kansai U-A, the WSLS strategy in the 8th block was observed in Problem B for Full-fb and it was observed in Problem D for Part-fb and Full-fb, as shown in Table 11. At Osaka SU, the WLSL strategy was not observed in Problem B, as shown in Table 12. For No-fb at Kansai U-A, the rate of correct answers is 0.60 in Problem B and it is 0.62 in Problem D, as shown in Table 16. According to Definition 1, we have the following result.

Result 1 *For the partial feedback treatment, subjects' learning was observed in Problem B at Kansai University (Group A) and Osaka Sangyo University. For no-feedback treatment, subjects' learning was observed in Problems B and D at Kansai University (Group A).*

In Group B, consider the cases of Problem B. The WSLS strategy in the 8th block was observed for Part-fb at Kansai U-B and Doshisha and for Full-fb at Kansai U-B, as shown in Tables 13, 14, and 15. For No-fb at Hiroshima CU, the rate of correct answers is 0.58 in the 8th block of 5 consecutive periods, as shown in Table 16. According to Definition 1, we have the following result.

Result 2 *At Kansai University (Group B) and Doshisha University, no learning by subjects was observed, but at Hiroshima City University, it was observed in Problem B for the full-feedback treatment.*

Table 11: Frequency of changing alternatives in B8: Kansai U-A (two-sided Fisher exact test).

Part-fb (20)				Full-fb (20)			
		0 point	40 points			0 point	40 points
Problem A	freq	28	72	Problem A	freq	23	77
	switch	14	19		switch	12	13
	ratio	0.500	0.264		ratio	0.522	0.169
	p-value		**0.033**		p-value		**0.010**
Problem B	freq	45	55	Problem B	freq	47	53
	switch	13	10		switch	18	5
	ratio	0.289	0.182		ratio	0.383	0.094
	p-value		0.238		p-value		<**0.001**
Problem C	freq	34	66	Problem C	freq	24	76
	switch	14	21		switch	10	21
	ratio	0.412	0.318		ratio	0.417	0.276
	p-value		0.382		p-value		0.213
Problem D	freq	37	62	Problem D	freq	46	54
	switch	21	46		switch	21	13
	ratio	0.324	0.742		ratio	0.457	0.241
	p-value		<**0.001**		p-value		**0.034**

Table 12: Frequency of changing alternatives in B8: Osaka SU (two-sided Fisher exact test).

Part-fb (10)				Full-fb (10)			
		0 point	40 points			0 point	40 points
Problem A	freq	18	32	Problem A	freq	11	37
	switch	7	4		switch	5	7
	ratio	0.389	0.125		ratio	0.455	0.189
	p-value		**0.041**		p-value		0.113
Problem B	freq	21	29	Problem B	freq	18	32
	switch	6	6		switch	8	8
	ratio	0.286	0.207		ratio	0.444	0.250
	p-value		0.738		p-value		0.211
Problem C	freq	13	37	Problem C	freq	17	33
	switch	6	2		switch	8	13
	ratio	0.462	0.054		ratio	0.471	0.394
	p-value		**0.002**		p-value		0.764
Problem D	freq	27	23	Problem D	freq	17	33
	switch	12	9		switch	6	15
	ratio	0.444	0.391		ratio	0.353	0.455
	p-value		0.779		p-value		0.557

Table 13: Frequency of changing alternatives in B8: Kansai U-B (two-sided Fisher exact test).

Part-fb				Full-fb			
		0 point	40 points			0 point	40 points
Problem A	freq	45	90	Problem A	freq	46	99
(n =27)	switch	17	30	(n =29)	switch	21	24
	ratio	0.378	0.333		ratio	0.457	0.242
	p-value		0.702		p-value		**0.012**
Problem B	freq	54	76	Problem B	freq	87	123
(n =26)	switch	25	8	(n =43)	switch	46	22
	ratio	0.463	0.105		ratio	0.529	0.179
	p-value		<**0.001**		p-value		<**0.001**

Table 14: Frequency of changing alternatives in B8: Doshisha (two-sided Fisher exact test).

Part-fb				Full-fb			
		0 point	40 points			0 point	40 points
Problem A	freq	37	103	Problem A	freq	25	75
(n =28)	switch	11	38	(n =20)	switch	10	20
	ratio	0.297	0.369		ratio	0.400	0.267
	p-value		0.547		p-value		0.218
Problem B	freq	41	59	Problem B	freq	46	52
(n =20)	switch	17	12	(n =20)	switch	19	14
	ratio	0.415	0.203		ratio	0.413	0.269
	p-value		**0.027**		p-value		0.142

Table 15: Frequency of changing alternatives in B8: Hiroshima CU (two-sided Fisher exact test).

Part-fb				Full-fb			
		0 point	40 points			0 point	40 points
Problem A	freq	30	85	Problem A	freq	29	76
(n =23)	switch	11	34	(n =21)	switch	15	18
	ratio	0.367	0.400		ratio	0.517	0.237
	p-value		0.830		p-value		**0.009**
Problem B	freq	48	49	Problem B	freq	35	65
(n =20)	switch	22	13	(n =20)	switch	11	14
	ratio	0.458	0.265		ratio	0.314	0.215
	p-value		0.059		p-value		0.335

Table 16: Average rate of correct answer.

	FR_1	No-fb	Part-fb	Full-fb	FR_8	No-fb	Part-fb	Full-fb
Kansai U-A	Problem A	0.530	0.630	0.680	Problem A	0.590	0.660	0.760
	Problem B	0.380	0.450	0.440	Problem B	**0.600**	0.710	0.790
	Problem C	0.690	0.530	0.560	Problem C	**0.730**	0.640	0.650
	Problem D	0.430	0.510	0.550	Problem D	**0.620**	0.770	0.750
Osaka SU	Problem A	0.700	0.720	0.580	Problem A	**0.660**	0.820	0.660
	Problem B	0.460	0.440	0.620	Problem B	0.380	0.820	0.760
	Problem C	0.660	0.700	0.600	Problem C	**0.680**	0.740	0.720
	Problem D	0.480	0.440	0.400	Problem D	0.560	0.480	0.620
Kansai U-B	Problem A	0.680	0.593	0.641	Problem A	**0.733**	0.556	0.683
	Problem B	0.452	0.492	0.493	Problem B	0.519	0.800	0.707
Doshisha	Problem A	0.622	0.614	0.670	Problem A	0.585	0.536	0.750
	Problem B	0.490	0.500	0.490	Problem B	**0.620**	0.770	0.630
Hiroshima CU	Problem A	0.560	0.626	0.571	Problem A	0.570	0.617	0.667
	Problem B	0.420	0.510	0.430	Problem B	0.580	0.610	0.710

Note: The boldfaced values for No-fb indicate that subjects learned the correct answer, according to Definition 1 (3).

4.2 Meaningful Learning and WSLS Strategy

Let us proceed to the main part of this paper. In this subsection, we state our observations answering to the hypotheses we presented in Section 1. Recall that FR_k^i represents the relative frequency of periods in which subject i chose the correct answer within the k-th block of 5 consecutive periods. Let FR_1 and FR_9 denote the vectors whose i-th component is FR_1^i and FR_9^i, respectively. As noted in the second paragraph of subsection 3, subjects were randomly assigned to sessions at each site. Thus, for each binary choice problem, we can apply the test for the differences between the means of FR_1 and FR_9, referring to the subjects who are faced with the binary choice problem in the 1st block as "inexperienced" subjects, and also refer to those in the 9th block as "experienced" subjects.

Definition 2 *For each binary choice problem, we consider that subjects who have learned in the binary choice problem meaningfully learned the underlying structure of weighted voting games if (a) the elements of* FR_9 *of experienced subjects are, on average, significantly larger than those of* FR_1 *of inexperienced subjects, (b) the WSLS strategy is not observed in the 9th and 12th blocks for the partial-feedback or full-feedback treatments, (c) the rates of correct answers are at least 60% in the 9th and 12th blocks, regardless of feedback treatments.*

If subjects were confident in what they had learned up to the 40th period, they would not engage in the WSLS strategy in the 9th block. Even in that case, however, if the WSLS strategy was observed in the 12th block, then the conviction should have fluctuated. In this case, we do not consider that they meaningfully learned. For No-fb, we require correct answer rates of 60% or higher, because the correct answer rate would be 50% even by random choice. Eventually, in Definition 2, we added conditions (b) and (c) to the definition made in Guerci et al. (2017).

Definition 2 applied to behavior of subjects who learned in the binary choice problem. Accordingly, from Results 1 and 2, the candidates for the observation of meaningful learning are confined to Problem B for Part-fb at Kansai U-A and Osaka SU, Problems B and D for No-fb at Kansai U-A, and Problem B for Full-fb at Hiroshima CU. Note that in the 1st and 9th blocks different binary choice problems are provided with subjects, and thus we cannot compare the rates of correct answers between those blocks directly for each subject.

Instead, we adopted the following procedure. We thus compare the rates of correct answers between inexperienced subjects (FR_1) and experienced subjects (FR_9).

Tables 17 to 18 show the average rates of correct answers within 5 consecutive periods for inexperienced and experienced subjects (the average values of elements of FR_1 and FR_9) for each binary choice problem. Those tables also list the p-values for the Brunner-Munzel test, where the null hypothesis is that the elements of FR_9 are, on average, the same as those of FR_1. In Problem D for No-fb at Kansai U-A, the rate of correct answers is 0.620 in the 9th block, and it is 0.660 in the 12th block, and the p-value for the Brunner-Muzel test is 0.031, and thus meaningful learning was observed. In Problem B for No-fb at Kansai U-A, however, the rate of correct answers is 0.500 in the 9th block, and the p-value for the Brunner-Muzel test is 0.243, and thus meaningful learning was not observed.

As for the other candidates for meaningful learning, in Problem B for Part-fb at Kansai U-A and Osaka SU and Problem B for Full-fb at Hiroshima CU, we observed that subjects chose the WSLS strategy, as shown in Tables 20 to 29 in Appendix B. Those tables also show the WSLS strategy was chosen by subjects in many experimental sessions in both Part-fb and Full-fb. Therefore, we conclude as follows.

Observation 1 *Hypothesis 1 was affirmatively confirmed.*

From Result 1, learning by subjects was observed in Problem B for Part-fb at Kansai U-A and Osaka SU and in Problem B for No-fb at Kansai U-A, but the p-values of the Brunner-Munzel test in Table 17 show that the increase in the rate of correct answers were not significant; condition (a) in Definition 2 was not satisfied for each case. In Problem D for No-fb at Kansai U-A both conditions (a), (b), and (c) were satisfied. (The average rates of correct answer was 0.60 in 9th block and 0.66 in 12th block.) Thus, meaningful learning was observed. From Result 2, learning by the subjects was observed only for no-feedback and full-feedback treatments at Hiroshima CU, but Table 18 shows that condition (a) was not satisfied. In summary, we have the following results, according to statistical analyses the results of which are shown in those tables.

Result 3 *Meaningful leaning was not observed at Osaka Sangyo University for any binary choice problems in any treatments, while it was observed at Kansai University (Group A) in Problem D for no-feedback treatment.*

Result 4 *Meaningful leaning was not observed at Kansai University (Group B), Doshisha University, and Hiroshima City University for any binary choice problems in any treatments.*

Table 17: Average rate of correct answer: Kansai U-A, Osaka SU.

	Kansai U-A			Osaka SU		
Problem A	No-fb	Part-fb	Full-fb	No-fb	Part-fb	Full-fb
Inexperienced (FR_1)	0.530	0.630	0.680	0.700	0.720	0.580
Experienced (FR_9)	0.670	0.500	0.560	0.620	0.480	0.380
p-value	0.089	0.316	0.322	0.682	0.166	0.313
Experienced (FR_{12})	0.770	0.430	0.640	0.700	0.500	0.560
Problem B	No-fb	Part-fb	Full-fb	No-fb	Part-fb	Full-fb
Inexperienced (FR_1)	0.380	0.450	0.440	0.460	0.440	0.620
Experienced (FR_9)	0.500	0.540	0.490	0.360	0.440	0.500
p-value	0.243	0.260	0.466	0.328	0.971	0.323
Experienced (FR_{12})	0.640	0.430	0.650	0.440	0.740	0.720
Problem C	No-fb	Part-fb	Full-fb	No-fb	Part-fb	Full-fb
Inexperienced (FR_1)	0.690	0.530	0.560	0.660	0.700	0.600
Experienced (FR_9)	0.620	0.640	0.730	0.740	0.620	0.540
p-value	0.777	0.206	**0.034**	0.498	0.449	0.625
Experienced (FR_{12})	0.680	0.610	0.780	0.740	0.680	0.640
Problem D	No-fb	Part-fb	Full-fb	No-fb	Part-fb	Full-fb
Inexperienced (FR_1)	0.430	0.510	0.550	0.480	0.440	0.400
Experienced (FR_9)	0.620	0.610	0.510	0.200	0.380	0.600
p-value	**0.031**	0.182	0.560	**0.024**	0.456	0.103
Experienced (FR_{12})	0.630	0.670	0.740	0.220	0.540	0.600

Note: Learning was not observed in Problem C for Full-fb at Kansai U-A and Problem D for No-fb at Osaka S-U. (See Result 1.) For No-fb at Kansai U-A, the rate of correct answers is 0.620 in the 9th block, and it is 0.680 in the 12th block (which is not shown in the table). The p-values for the Brunner-Munzel test are provided. Emboldened values indicate rejection of the null hypothesis at the 5% significance level.

As shown in Table 5, the Raven scores of the subjects at Kansai U-A (about 11.2 on average) are significantly higher than those of subjects at Osaka SU (about 10.6 on average). The average Raven score of subjects at Doshisha is about 11.6. The Raven scores of the subjects at Kansai U-B (about 11.5 on average) are significantly higher than those of subjects at Hiroshima CU (about 11.0 on average).

Guerci et al. (2017) considered that subjects meaningfully learned the underlying structure of weighted voting if condition (a) is satisfied in Definition 2. Confirm that learning

Table 18: average rate of correct answer: Kansai U-B, Doshisha, Hiroshima CU.

	Kansai U-B			Doshisha			Hiroshima CU		
Problem A	No-fb	Part-fb	Full-fb	No-fb	Part-fb	Full-fb	No-fb	Part-fb	Full-fb
Inexperienced (FR_1)	0.680	0.593	0.641	0.622	0.614	0.670	0.560	0.626	0.571
Experienced (FR_9)	0.689	0.685	0.586	0.690	0.610	0.560	0.590	0.410	0.560
p-value	0.840	0.136	0.632	0.305	0.885	0.258	0.569	**<0.001**	0.891
Experienced (FR_{12})	0.634	0.810	0.676	0.690	0.600	0.640	0.650	0.550	0.670

Problem B	No-fb	Part-fb	Full-fb	No-fb	Part-fb	Full-fb	No-fb	Part-fb	Full-fb
Inexperienced (FR_1)	0.452	0.492	0.493	0.490	0.500	0.490	0.420	0.510	0.430
Experienced (FR_9)	0.538	0.563	0.469	0.541	0.636	0.460	0.520	0.548	0.571
p-value	0.231	0.270	0.761	0.581	**0.039**	0.517	0.235	0.475	0.069
Experienced (FR_{12})	0.501	0.732	0.791	0.541	0.836	0.640	0.620	0.739	0.676

Note: Learning was not observed in Problem A for Part-fb at Hiroshima CU and Problem B for Part-fb at Doshisha. (See Result 2). The p-values for the Brunner-Munzel test are provided. Emboldened values indicate rejection of the null hypothesis at the 5% significance level.

and meaningful learning would be observed in Problem B for Part-fb at Doshisha, if we dropped additional conditions for the WSLS strategy and applied the original definitions for leaning and meaningful learning made by Guerci et al. (2017). Let us say that subjects who have learned in binary choice problems meaningfully learned the underlying structure of weighted voting games in a weaker sense, when condition (1) in Definition 1 and condition (a) in Definition 2 were satisfied. Even in this weaker sense, meaningful learning was not observed in Problem B for part-fb at Osaka SU (Tables 9 and 17) and in Problem B for No-fb and Full-fb at Hiroshima CU (Tables 10 and 18), although it was observed at Doshisha as well as Kansai U-A, In summary, we have the following result.

Result 5 *In a bandit experiment in the context of weighted voting, meaningful leaning of the underlying structure of weighted voting in a weaker sense was observed at experimental sited where subjects' ability for pattern recognition was relatively high.*

In Problems B and D for No-fb, meaningful learning was observed at Osaka University and the University of Tsukuba (Guerci et al., 2017). The average Raven scores of subjects were 12.3 and 12.5, respectively.[10] Note that meaningful learning was observed for No-fb at Osaka University and the University of Tsukuba.[11] Result 5 is consistent with the result shown in Guerci et al. (2017).

[10]The Raven scores of the subjects were not mentioned in the paper, but the data on their Raven scores are available upon request.

[11]See Fig. 4 in Guerci et al. (2017) and Figure 1 in Watanabe (2018) for time series plots of those rates.

Note that the male-to-female ratios of subjects, age, subjects' affiliation (sci-eng, econ, others) did not significantly affect success or failure of meaningful learning at each experimental site. Recall Hypothesis 2 that meaningful learning of the underlying structure of weighted voting is observed at experimental site where subjects have relatively higher ability for pattern recognition, when the immediate payoff-related feedback information was withheld. Result 5 implies the following observation.

Observation 2 *Hypothesis 2 was affirmatively confirmed.*

In effect, there might be an affirmative relationship between subjects' ability for recognizing the pattern of payoffs and their ability for generalizing their knowledge they obtained from their experiences to a similar but different situation. Watanabe (2018) reconfirmed meaningful learning in Problem D without any feedback information at Osaka University, even though the correct answer was changed from Choice 1 in the first part to Choice 2 in the second part. The Raven scores of the subjects recruited at Osaka University was about 12.3 on average there. Thus, our result is robust.

Finally, we examine Hypothesis 3 extracted from outcomes in Guerci et al. (2017). In Problems A and C, a committee has two "large" voters who can form an MWC on their own, while the other committee does not. In Problems B and D, there is no such a clear difference between the two committees, and in this sense it is more difficult to find the correct answer. From Results 3 and 4, meaningful learning was observed only in Problem D for No-fb, where subjects experienced in Problem C in the first 40 periods. Note again that Guerci et al. (2017) observed meaningful learning only in Problems B and D for No-fb and Watanabe (2018) also observed it only in Problem D for No-fb. Subjects who had experienced easy binary choice problems in early periods might meaningfully learn the underlying structure of weighted voting; otherwise, they failed to meaningfully learn it (Hypothesis 3).

We presume that a subject chose options according to some systematic rule, unless the number of runs in a sequence of options he or she chose was considered as a random variable. The runs test is applied to a sequence of options each identical subject chose, but 5 consecutive choices in each block are too few as the sample; we applied the test to the sequence of options each subject chose in periods 21-40 and in periods 41-60, respectively. As stated in Result 3, meaningful learning was observed at Kansai U-A in Problem D for

No-fb. Table 19 presents numbers of subjects each of whom is counted if the null hypothesis was rejected in the sequences of Problems C and D at Kansai U-A.

Table 19: Number of subjects who chose options systematically: runs test.

	periods 21-40	periods 41-60
Problem C	8	8
Problem D	11	9

Note: Numbers of subjects each of whom is counted if the null hypothesis was rejected in Problems C and D for No-fb at Kansai U-A, where the null hypothesis is that the number of runs in a sequence of options each subject chose in periods 21-40 (Inexperienced) (in periods 41-60 (Experienced)) is a random variable. The sample size is 20 for each sample.

We included the number of subjects who chose the correct option in all 20 periods in the number of subjects for each of whom the null hypothesis was rejected.[12] The number of the rejections increased from 8 to 9 when subjects were faced with Problem C in periods 21-40 and then Problem D in periods 41-60, while it decreased from 11 to 8 when they were faced with binary choice problems in the reverse order. This tendency became much clearer if we counted the number of subjects who chose the wrong option in all 20 consecutive periods; there are 4 such cases in periods 21-40 and 2 cases in periods 41-60 in Problem D.

From the facts noted above, it is inferred that subjects who had chosen options in Problem C in early periods according to systematic search rules could choose options in Problem D in the following periods also according to those rules, but some subjects who were faced with Problem D in early periods might abandon their systematic search rules of correct option in the following periods. Thus, we conclude as follows.

Observation 3 *Hypothesis 3 was reconfirmed with a fact on subjects' search behavior.*

An environment in which subjects could deeply infer the underlying structure of weighted voting was the one in which they experienced easy binary choice problems in early periods. Subjects failed to meaningfully learn it when they experienced difficult binary choice problems in those early periods. Further investigation should have been desirable for detecting some possible factors behind Hypothesis 3, if it was possible under the current specification in this experiment.

[12]Note that the null hypothesis is not rejected as often in the runs test, even if the sequence of options a subject chooses is generated by some systematic rule, when, e.g., he or she makes an experimental choice only once or twice.

5 Conclusion and Remarks

In the literature of meaningful learning, Weber (2003) had already found that withholding feedback information induced meaningful learning (introspective thinking) in a competitive guessing game. Some researchers currently pursue a neuroscientific aspect of meaningful learning without any feedback information. This paper confined attention to the questions about why subjects could not meaningfully learn the latent feature of weighted voting even with feedback information.

As a discussion issue, we would like to ask whether people can deeply infer from their experiences the underlying relationship between the actual voting powers and the nominal voting weights. It is easy to see that meaningful learning was not observed even in a weaker sense at Osaka Sangyo University and Hiroshima City University. Recall that the average Raven score of the non-student general public was about 8.0 as shown in Table 7 and that subjects at those two universities have significantly higher Raven scores on average than do non-student general public. Observation 2 may thus imply that meaningful learning by non-student general public would not be observed if they participated in this experiment.

However, we found some features of the difficulty in meaningful learning. Immediate feedback information about subjects' payoffs might confuse their inference on the relationship between nominal voting weights and actual payoffs so that they took the win-stay-lose-shift strategy (Observation 1). Rather, withholding feedback information promoted meaningful leaning by college students, although they had significantly higher scores for pattern recognition measured by Raven's test than non-student general public.

We confirmed that there is an affirmative relationship between subjects' ability for recognizing the pattern of payoffs and their ability for generalizing their knowledge they obtained from their experiences to a similar but different situation (Observation 2). We could also find an environment in which people can deeply infer the latent feature of weighted voting in order to use weighted voting better. In this experiment, we reconfirmed a fact extracted from outcomes in Guerci et al. (2017) that subjects who have experienced easier binary choice problems in early periods could meaningfully learn the underlying structure of weighted voting, but they failed to meaningfully learn it when they have experienced more difficult binary choice problems in the early periods (Observation 3).

Further study is desirable for Observation 3. Subjects might abandon their deep inference on the latent feature of binary choice problems, when they were faced with difficult binary choice problems. Even if they learned something from their experiences, they might not be able to generalize what they had learned to another similar but different binary choice problem. We need to design another experiment for detecting these complex factors.

Finally, we would like to post a topic for future research. Is there any feedback information that induces subjects to meaningfully learn the underlying structure of weighted voting? In this experiment, subjects were prohibited from taking any notes during the sessions. By this lack of sufficient memory on the outcomes that were realized by their previous choices, immediate payoff-related feedback information might confuse subjects' inference. We will confirm this hypothesis in another experiment.

Declarations

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Conflict of Interest

The authors declare that they have no conflict of interest.

Availability of Data and Codes

All raw and processed data are available upon requests. All data were processed with STATA and any codes were saved as ado files. Those codes are available upon requests.

Ethical Approval

All procedures performed in studies involving human participants were 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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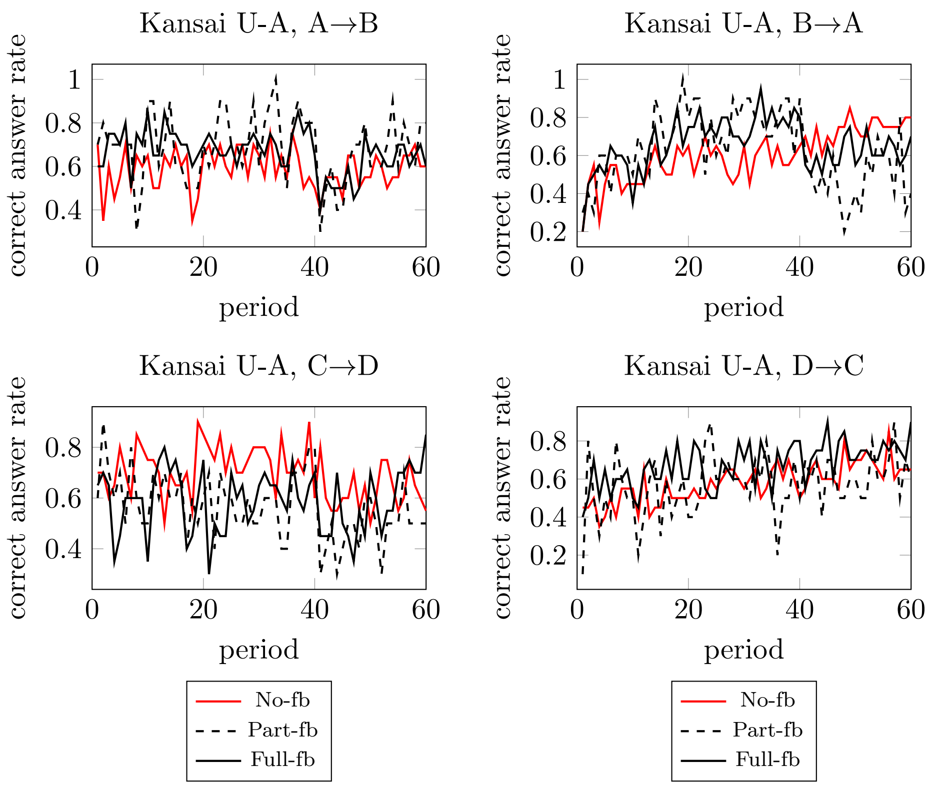
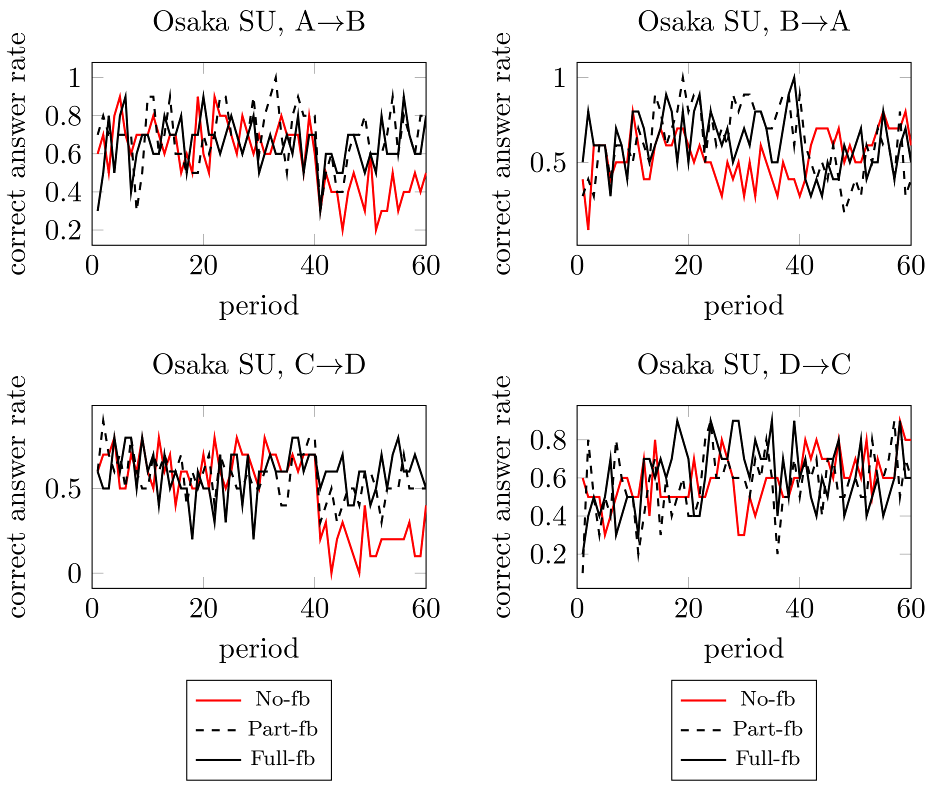
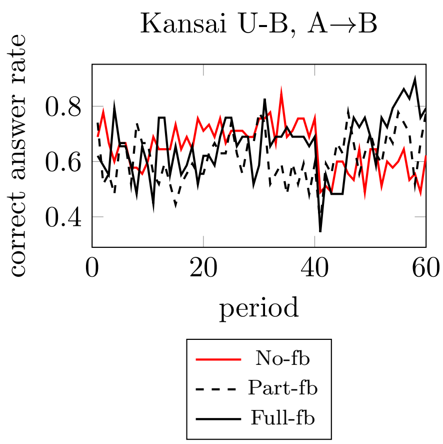
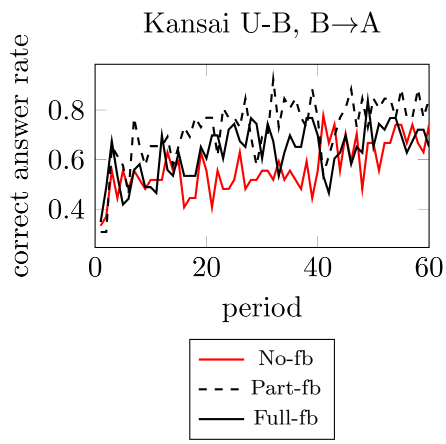
Appendix A: Time Series Plots

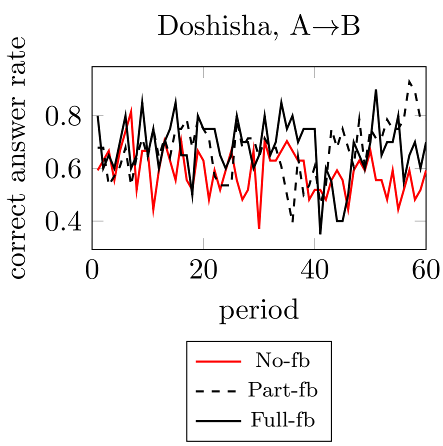
Below are the time series plots of the rates of correct answers subjects chose for each treatment at each site. In each figure, the horizontal axis stands for the periods from the 1st period to the 60th period, and the vertical axis represents the percentage of correct answers in each period. The same diagrams are provided also in Appendix B of a discussion paper version of this paper (Ogawa et al., 2020).

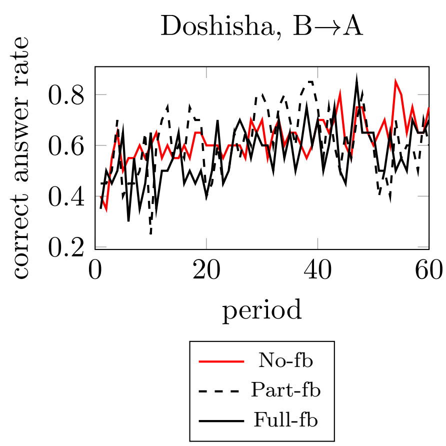

Kansai U-A, A→B
Kansai U-A, B→A
Kansai U-A, C→D
Kansai U-A, D→C
correct answer rate
period
No-fb
Part-fb
Full-fb

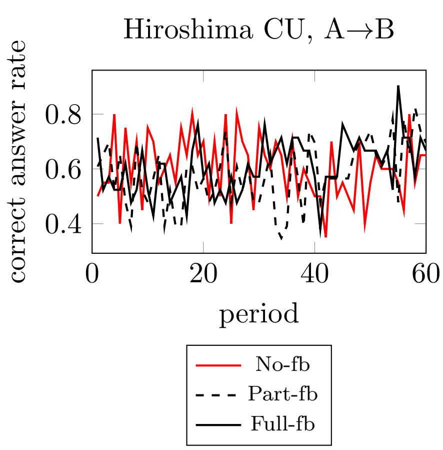

Osaka SU, A→B
Osaka SU, B→A
Osaka SU, C→D
Osaka SU, D→C
correct answer rate
period
No-fb
Part-fb
Full-fb

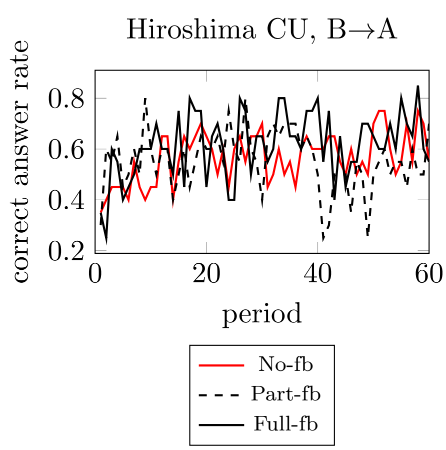

Kansai U-B, A→B
correct answer rate
0.4
0.6
0.8
0
20
40
60
period
No-fb
Part-fb
Full-fb


Kansai U-B, B→A
correct answer rate
0.4
0.6
0.8
0
20
40
60
period
No-fb
Part-fb
Full-fb


Doshisha, A→B
correct answer rate
0.4
0.6
0.8
0
20
40
60
period
No-fb
Part-fb
Full-fb


Doshisha, B→A
correct answer rate
0.2
0.4
0.6
0.8
0
20
40
60
period
No-fb
Part-fb
Full-fb


Hiroshima CU, A→B
correct answer rate
0.4
0.6
0.8
0
20
40
60
period
No-fb
Part-fb
Full-fb


Hiroshima CU, B→A
correct answer rate
0.2
0.4
0.6
0.8
0
20
40
60
period
No-fb
Part-fb
Full-fb

Appendix B: Detecting the WSLS Strategy in B9 and B12

The following tables show the frequency of scores (freq), the frequency of switching answers (switch) and their ratio (ratio), and the p-value for the two-sided Fisher's exact test. The null hypothesis is that switching choices immediately after observing 0 points and switching choices immediately after observing 40 points were equally likely to be observed.

Table 20: Frequency of changing alternatives in B9: Kansai U-A (two-sided Fisher test).

Part-fb (20)				Full-fb (20)			
		0 point	40 points			0 point	40 points
Problem A	freq	17	63	Problem A	freq	21	59
	switch	7	7		switch	10	6
	ratio	0.412	0.111		ratio	0.476	0.102
	p-value		**0.008**		p-value		<**0.001**
Problem B	freq	44	36	Problem B	freq	39	41
	switch	21	7		switch	24	14
	ratio	0.477	0.194		ratio	0.615	0.341
	p-value		**0.010**		p-value		**0.025**
Problem C	freq	25	55	Problem C	freq	26	53
	switch	8	10		switch	11	14
	ratio	0.320	0.182		ratio	0.423	0.264
	p-value		0.247		p-value		0.200
Problem D	freq	37	43	Problem D	freq	38	42
	switch	15	14		switch	20	11
	ratio	0.405	0.326		ratio	0.526	0.262
	p-value		0.492		p-value		**0.022**

Table 21: Frequency of changing alternatives in B9: Osaka SU (two-sided Fisher test).

Part-fb (10)				Full-fb (10)			
		0 point	40 points			0 point	40 points
Problem A	freq	12	28	Problem A	freq	13	27
	switch	5	7		switch	4	9
	ratio	0.416	0.250		ratio	0.307	0.333
	p-value		0.453		p-value		> 0.999
Problem B	freq	28	12	Problem B	freq	18	21
	switch	12	1		switch	12	3
	ratio	0429	0.083		ratio	0.667	0.143
	p-value		0.318		p-value		<**0.001**
Problem C	freq	9	31	Problem C	freq	15	25
	switch	5	15		switch	7	11
	ratio	0.556	0.484		ratio	0.467	0.440
	p-value		>0.999		p-value		> 0.999
Problem D	freq	24	15	Problem D	freq	25	15
	switch	11	3		switch	13	5
	ratio	0.458	0.200		ratio	0.520	0.333
	p-value		0.171		p-value		0.332

Table 22: Frequency of changing alternatives in B12: Kansai U-A (two-sided Fisher test).

Part-fb (20)				Full-fb (20)			
		0 point	40 points			0 point	40 points
Problem A	freq	25	75	Problem A	freq	22	78
	switch	5	10		switch	3	5
	ratio	0.200	0.133		ratio	0.136	0.064
	p-value		0.518		p-value		0.369
Problem B	freq	36	64	Problem B	freq	53	47
	switch	14	11		switch	16	8
	ratio	0.389	0.172		ratio	0.302	0.170
	p-value		**0.029**		p-value		0.161
Problem C	freq	30	70	Problem C	freq	22	78
	switch	11	20		switch	10	14
	ratio	0.367	0.286		ratio	0.455	0.179
	p-value		0.482		p-value		**0.012**
Problem D	freq	45	55	Problem D	freq	51	49
	switch	18	11		switch	18	7
	ratio	0.400	0.200		ratio	0.353	0.143
	p-value		**0.045**		p-value		**0.021**

Table 23: Frequency of changing alternatives in B12: Osaka SU (two-sided Fisher test).

Part-fb (10)				Full-fb (10)			
		0 point	40 points			0 point	40 points
Problem A	freq	9	41	Problem A	freq	16	34
	switch	4	12		switch	5	12
	ratio	0.444	0.293		ratio	0.313	0.353
	p-value		0.442		p-value		>0.999
Problem B	freq	22	28	Problem B	freq	23	26
	switch	9	3		switch	9	6
	ratio	0409	0.107		ratio	0.391	0.231
	p-value		0.050		p-value		0.352
Problem C	freq	16	34	Problem C	freq	15	35
	switch	5	7		switch	5	9
	ratio	0.314	0.206		ratio	0.333	0.257
	p-value		0.486		p-value		0.733
Problem D	freq	27	23	Problem D	freq	21	29
	switch	8	4		switch	9	6
	ratio	0.296	0.174		ratio	0.429	0.207
	p-value		0.526		p-value		0.251

Table 24: Frequency of changing alternatives in B9: Kansai U-B (two-sided Fisher test).

Part-fb				Full-fb			
		0 point	40 points			0 point	40 points
Problem A	freq	35	69	Problem A	freq	48	120
(n =26)	switch	17	12	(n =43)	switch	25	22
	ratio	0.486	0.174		ratio	0.521	0.183
	p-value		**0.001**		p-value		<**0.001**
Problem B	freq	57	51	Problem B	freq	58	58
(n =27)	switch	29	12	(n =29)	switch	36	16
	ratio	0.509	0.235		ratio	0.621	0.276
	p-value		**0.005**		p-value		<**0.001**

Table 25: Frequency of changing alternatives in B9: Doshisha (two-sided Fisher test).

Part-fb				Full-fb			
		0 point	40 points			0 point	40 points
Problem A	freq	21	59	Problem A	freq	23	56
(n =20)	switch	7	21	(n =20)	switch	12	16
	ratio	0.333	0.356		ratio	0.522	0.286
	p-value		>0.999	p-value			0.069
Problem B	freq	49	63	Problem B	freq	33	47
(n =28)	switch	21	13	(n =20)	switch	19	16
	ratio	0.429	0.206		ratio	0.576	0.340
	p-value		**0.014**		p-value		**0.043**

Table 26: Frequency of changing alternatives in B9: Hiroshima CU (two-sided Fisher test).

Part-fb				Full-fb			
		0 point	40 points			0 point	40 points
Problem A	freq	22	55	Problem A	freq	26	54
(n =20)	switch	14	25	(n =20)	switch	12	18
	ratio	0.636	0.455		ratio	0.462	0.333
	p-value		0.208		p-value		0.327
Problem B	freq	45	47	Problem B	freq	38	46
(n =23)	switch	22	7	(n =21)	switch	20	10
	ratio	0.489	0.149		ratio	0.526	0.217
	p-value		<**0.001**		p-value		**0.006**

Table 27: Frequency of changing alternatives in B12: Kansai U-B (two-sided Fisher test).

Part-fb				Full-fb			
		0 point	40 points			0 point	40 points
Problem A	freq	32	98	Problem A	freq	46	169
(n =26)	switch	10	21	(n =43)	switch	21	35
	ratio	0.313	0.214		ratio	0.457	0.207
	p-value		0.339		p-value		0.001
Problem B	freq	64	71	Problem B	freq	58	87
(n =27)	switch	24	12	(n =29)	switch	27	8
	ratio	0.375	0.169		ratio	0.466	0.092
	p-value		**0.011**		p-value		<**0.001**

Table 28: Frequency of changing alternatives in B12: Doshisha (two-sided Fisher test).

Part-fb				Full-fb			
		0 point	40 points			0 point	40 points
Problem A	freq	21	79	Problem A	freq	34	66
(n =20)	switch	6	19	(n =20)	switch	18	15
	ratio	0.286	0.241		ratio	0.529	0.227
	p-value		0.778		p-value		**0.003**
Problem B	freq	67	73	Problem B	freq	48	52
(n =28)	switch	24	15	(n =20)	switch	25	13
	ratio	0.358	0.205		ratio	0.521	0.250
	p-value		0.059		p-value		**0.007**

Table 29: Frequency of changing alternatives in B12: Hiroshima CU (two-sided Fisher test).

Part-fb				Full-fb			
		0 point	40 points			0 point	40 points
Problem A	freq	31	65	Problem A	freq	26	73
($n = 20$)	switch	9	18	(n =20)	switch	14	16
	ratio	0.290	0.277		ratio	0.528	0.219
	p-value		>0.999		p-value		**0.005**
Problem B	freq	48	67	Problem B	freq	48	57
($n = 23$)	switch	24	19	($n = 21$)	switch	16	13
	ratio	0.500	0.284		ratio	0.333	0.228
	p-value		**0.021**		p-value		0.276

Appendix C: Instructions

The following instructions were used in sessions for Group B (Kansai U-B, Doshisha, Hiroshima CU) in which subjects were paid 50 JPY per correct answer in the Raven's test. For Group A (Kansai U-A, Osaka SU), subjects were paid a flat honorarium of 500 JPY for participation regardless of whether they answered the questions correctly. In bandit experiments, the instructions are remarkably simple, as compared with those in other economic or psychological experiments. The instructions for this experiment follow the standard format. The original version was written in Japanese and the main body was used also in sessions for Guerci et al. (2017).

Instructions

Welcome!

Thank you for participating in this experiment today. You will be paid 500 JPY for your participation and an additional reward that ranges from 0 to 3200 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 allocated to each of the four members of the committee (including you), and the number of votes required for a proposal to be approved. The number of votes you have will always be indicated with the label YOU.

Full-feedback treatment

There are a total of 60 periods. In each period, 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 period, you will receive zero points for that period. When a choice is made, the chosen committee will automatically allocate 120 points among the four members. The outcomes may vary from one period to another, but are based on a theory of decision-making in committees. Once the allocation is made, you will immediately be shown the resulting allocation. At the end of the experiment, you will be paid according to your total earnings during the 60 periods, at an exchange rate of 1 point = 1 JPY.

If you have any questions, please raise your hand.

Partial-feedback treatment

There are a total of 60 periods. In each period, you have 30 seconds to make your choice between the two committees. If you do not make any choice within the 30 seconds in one period, you will receive zero points for the period. When a choice is made, the chosen committee will automatically allocate 120 points among the four members. The outcomes may vary from one period to another, but they are based on a theory of decision-making in committees. Once the allocation is made, you will be shown the number of points allocated to you. You will not see the allocations to the other members of the committee. At the end of the experiment, you will be paid according to your total points at an exchange rate of 1 point = 1 JPY.

If you have any questions, please raise your hand.

No-feedback treatment

There are a total of 60 periods. In each period, you have 30 seconds to make your choice between the two committees. If you do not make any choice within the 30 seconds in one period, you will receive zero points for the period. When a choice is made, the chosen committee will automatically allocate 120 points between the four members. The outcomes may vary from one period to another, but they are based on a theory of decision-making in committees. You will not see the resulting allocation after each period. However, at the end of the experiment, you will be told the total points you have obtained during the 60 periods, and you will be paid according to the points earned over the 60 periods at an exchange rate of 1 point = 1 JPY.

If you have any questions, please raise your hand.