standard scales such as *Barratt's Impulsiveness Scale* (Bickel et al., 2001; Crean et al., 2002). Furthermore, neuroeconomic studies have revealed that addiction to drugs of abuse is strongly associated with delay discounting (Bickel et al., 2006; Ohmura et al., 2005).

Subjects also discount the value of uncertain rewards as the probability of receiving the rewards decreases (Rachlin et al., 1991; Reynolds et al., 2004; Ohmura et al., 2005). This behavioral tendency has been referred to as "probability discounting" (psychologically, also referred to as "uncertainty aversion" or "risk aversion"). Rachlin et al (1991) have proposed the following exponential and hyperbolic probability-discounting functions:

$$V_p = A\exp(-k_p O) \qquad (3)$$

and

$$V_p = A/(1+k_p O), \qquad (4)$$

where V_p is a subjective discounted value of a probabilistic reward, A is the value when $p = 1$, O is the odds against $= (1/p)-1$ (proportional to an average waiting time in a repeated gambling), and k_p is the probability discount rate. k_p indicates the degree to which one discounts the uncertain reward. Several studies found that hyperbolic probability discounting function (Equation 4) fits the behavioral data better than the exponential discount function (Equation 3). It can be said that k_p is a subject's uncertainty aversion parameter when $A > 0$ (gain); while k_p is an uncertainty-seeking parameter when $A < 0$ (loss). Hence, subjects with large k_p values prefer small likely rewards to large unlikely ones, but avoid small certain loss more strongly than large uncertain loss. In contrast to delay discounting, little is known regarding the relationship between probability discounting and self-reported impulsivity.

By employing these discounting frameworks, recent studies have reported that pathological gamblers discount delayed rewards more rapidly than controls (Petry, 2001a; Alessi et al., 2003; Dixon et al., 2003; Dixon et al., 2006, but see MacKillop et al., 2006). These studies demonstrated that there may be common neuropsychological processes between pathological gambling and addiction, since addicts also discount delayed rewards more rapidly than non-drug-dependent subjects (Bickel et al., 2001; Kirby et al., 1999; Richards et al., 1999; Reynolds et al., 2004; Ohmura et al., 2005; Passetti et al., 2007). However, to date, no study systematically employed delay and probability discounting framework in order to investigate neuropsychological processes underlying disadvantageous choices in the Iowa gambling task (IGT). Moreover, little is known concerning the relationship between gambling behavior and probability discounting. Only Holt, Green, and Myerson's study (2003) extensively studied the relationship between gambling and probability discounting in college students. They reported that gamblers discounted probabilistic rewards less steeply than non-gamblers, suggesting that gamblers are impulsive in the sense that they are less affected by risk than non-gamblers; on the other hand, gamblers did not discount delayed rewards more steeply than non-gamblers. Considering that little is known regarding the relationships between probability discounting of reward and punishment, and pathological gambling, it is important to further examine the relationship between pathological gambling and probability discounting. We next present our experimental data concerning the relationship between self-reported impulsivity, delay and probability discounting of gain and loss.

1.3 Experiment of delay and probability discounting

Participants

A total of 50 subjects participated in the present study. They are graduate or undergraduate students of a major national university in Japan. They were recruited through advertisements that were posted in the bulletin boards of university. The participants were informed that the experiment involved decision-making tasks on monetary gains and losses. They signed an informed consent form and received 1000 yen (about $10) after the experiment for participation.

Materials and Procedure

We used a computerized procedure to assess the degrees of delay and probability discounting. We also used hypothetical monetary outcomes because Johnson and Bickel (2002) showed a strong correlation between discounting rates for hypothetical and real monetary gains, and previous studies demonstrated that discounting rates for hypothetical and real money were not significantly different (Madden et al., 2003, 2004; Lagorio et al., 2005). The computerized task was composed of four types of discounting tasks (i.e. delay discounting of gain, probability discounting of gain, delay discounting of loss, probability discounting of loss).

Participants were seated individually in a quiet room and received the following simple instruction on the computer screen "From now, you are required to perform tasks of decision-making on monetary reward/loss. The task is to choose between two options. The monetary reward/loss in this experiment is hypothetical, but we want you to think as though it is real money." After that, they were received instructions about the four types of the tasks (delay discounting of gain, probability discounting of gain, delay discounting of loss, probability discounting of loss) with corresponding examples. After the instructions, they were asked to choose between the 2 cards displayed on the computer monitor. One card described money delivered immediately (or certainly, in the probability discounting tasks) and the other card described money delivered after a certain delay (or with a certain degree of probability, in the probability discounting tasks). The left card indicated the amounts of money that could be received (or lost, in the tasks of discounting of loss) immediately (or certainly, in the probability discounting tasks), and the right card was indicated 100,000 yen (about 1,000 dollars) that could be received (or lost, in the tasks of discounting loss) after a certain delay (or with a certain probability) The amount of money changed from 100,000 yen to 5,000 yen (from -100,000 yen to -5,000 yen, in loss-frame tasks) by 5000 yen and the delay changed within five values (1 week, 1 month, 6 months, 1 year, 5 years) and the probability also changed within five values (90%, 70%, 50%, 30%, 10%). These changes were computerized according to the algorithm of Richards et al. (1999b). This algorithm is designed to change the type of tasks and the amount of money in accordance with foregoing choices, and to discover the point that the preference of the participant switches from right to left (or from left to right). The value of the algorithm is it requires consistent responding in order to determine the indifference point. The switching point was regarded as an indifference point and used to analyze the data. In the present study, 20 indifference points (i.e. (Probability + Delay) X Gain-Loss) were determined. This algorithm is devised to mask the nature of procedure. In the present study, distracter trials were inserted after 10 indifference points were determined (for more details, see Richards et al. 1999b). The entire experiment procedure took about 0.5-1 h to complete.

Data analysis

Area Under the Curve (AUC) as discounting parameter

In order to determine the degree to which each subjects discounted delayed and uncertain monetary gains and losses, we adopted the Area Under the Curve (AUC; Myerson et al., 2001) for each of the four discounting tasks. The value of AUC is the area under a line graph made by plotting indifference points when normalizing the horizontal axis (delay or odds-against=1/probability-1) and the vertical axis (subjective value) (for the detail of calculation procedure, see Myerson et al., 2001; Ohmura et al., 2005). It should be noted that smaller AUC values indicate more dramatic discounting. The rationale for employing AUCs is as follows: (1) previous studies (Lane et al., 2003; Ohmura et al., 2006) have shown that the skewness of the distribution of AUCs is relatively small, in comparison to other discounting parameters calculated by fitting results to specific functions (e.g., hyperbolic *k*), and (2) because AUCs do not depend on a fitting function, there are no data loss and equation type-dependent systematic errors. Given that the purpose of the present-study was to investigate the relationship between discounting behavior and personality questionnaires rather than to determine the best discounting function to fit the data, AUCs appear to be an appropriate measure. It should be also noted that we used the algorithm devised by Richards et al. (1999) to prevent unreliable responses of participants because AUCs may reflect unreliable responses.

Additionally, we examined how the participants discounted the four types of monetary outcomes (delayed and probabilistic, gains and losses), because little has been known regarding whether delayed/ probabilistic losses are discounted hyperbolically, although it is well established that delayed and probabilistic gains are discounted hyperbolically, rather than exponentially (e.g. Mazur 1987; Rachlin et al. 1991; Richards et al. 1999b; Simpson and Vuchinich 2000). Specifically, we performed non-linear regression (SAS, PROC NLIN) to fit discounting functions (hyperbolic and exponential functions) to medians of indifference points at each delay or probability. To examine which equation better fits the data, we compare the R^2 values of the hyperbolic and exponential equations.

Personality questionnaires

Barratt's Impulsiveness Scale, version 11 (BIS-11: Patton et al., 1995)

The BIS-11 Japanese version (Someya et al., 2001) contains a total of 30 items and requires respondents to answer how frequently (rarely/never, occasionally, often, almost always/always) each statement applies to themselves. Because it has been shown that there are three factors (Patton et al., 1995), we analyzed the data using each factor, as well as the total score. Three factors are as follows: *Attentional Impulsiveness (AI)*, *Motor Impulsiveness(MI)* and *Nonplanning Impulsiveness(NI)* (Patton et al., 1995).

Sensation Seeking Scale (SSS, Form IV: Zuckerman et al., 1971)

We have also assessed subjects' sensation seeking (Zuckerman 1979; Harmsen et al., 2006). The SSS (Form IV) Japanese version (Terasaki et al., 1987) contains a total of 38 items, although the original SSS contains 72 items. It should be noted that this revision by Terasaki et al. (1987) is based on the results of a factor analysis with a large sample size (N=889), with the validity of Japanese version being confirmed in a second study (Terasaki et al., 1988). This questionnaire requires respondents to choose one of two statements that best applies to themselves. There are four dimensions: *Thrill and Adventure Seeking (TA)*, "a desire to engage in sports or activities involving speed or danger"; *Experience Seeking (ES)*, "the seeking of experience through the mind and senses, travel and a nonconforming life style"; *Disinhibition (DI)*, "the desire for social and sexual disinhibition"; and *Boredom Susceptibility*, "an aversion to repetition, routine, and dull people, and restlessness when things are unchanging" (Zuckerman, 1971). We analyzed the data using each factor, in addition to the total score.

In order to examine the relationship between self-reported impulsivity and the four types of discounting behavior, we conducted correlation analyses between them. Pearson's product-moment correlation coefficients were utilized for examining the relationships between the AUCs of four types of discounting behavior. Because self-reported impulsivity scale scores did not normally distributed, Spearman's rank-order correlation coefficients were calculated for the relationships between Barratt's Impulsiveness Scale/Sensation Seeking Scale and the degrees of the four types of discounting behavior parameterized with AUC Furthermore, the relationships of the factors in each scale to the four types of discounting behavior were also examined in the same manner. Significant level was set at 5% throughout.

Results

Goodness of Fit for Hyperbolic & Exponential Functions

All the R^2 values of the hyperbolic function for the group data (>0.97) were larger than those of the exponential function (<0.95), indicating that the subjects discounted all of the four types of monetary outcomes (i.e., delayed and probabilistic gains and losses) hyperbolically, rather than exponentially, as a number of previous studies have reported (e.g. Rachlin et al. 1991; Richards et al. 1999; Bickel et al. 1999, Takahashi, 2005).

Correlation between Delay and Probability Discounting of gain and loss

There was a significant positive correlation between delay discounting of gains and losses ($r=0.47$, $p<.01$). On the contrary, there was a significant negative correlation between probability discounting of gains and losses ($r=-0.48$, $p<.01$). In other words, subjects who strongly discounted uncertain gains dramatically avoided possible losses. This indicates that subject who prefers large uncertain rewards to small certain ones do not seriously consider potential danger with small probabilities.

For gains, delay and probability discounting were positively correlated ($r=0.27$, $p<.01$); in contrast, for losses, delay and probability discounting were not significantly correlated ($p>.05$). This implies that distinct neuropsychological processes may mediate probability discounting of gains and losses

Relationship between Self-reported impulsivity and discounting behavior

Spearman's rank correlation coefficients between self-reported impulsivity (i.e., BIS and SSS) and the four types of discounting behavior (parametrized with AUC) are presented in Table 1. It is to be noted that smaller AUC values correspond to stronger (i.e., steeper) discounting. Therefore, a negative correlation between the self-reported impulsivity scale and AUC is equivalent to a positive correlation between the scale and discounting. We observed that BIS was significantly correlated with delay discounting of losses and SSS was significantly associated with probability discounting of gains.

We further examined the relationships between the four types of discounting behavior and factors in BIS (Table 2) and SSS (Table 3). Generally, factors in BIS were more strongly related to discounting behavior. Because probability discounting is considerably related to gambling behavior, we now focus on the relations regarding probability discounting. Attentional impulsiveness (AI) in BIS and Thrill and Adventure seeking (TA) in SSS were significantly correlated with the AUC of probability discounting of gain, implying that subjects with high AI and TA prefer large uncertain gains to small certain ones, which may result in gambling behavior. Additionally, it is natural that nonplanning impulsiveness (NI) was associated with rapid discounting of delayed gains (smaller AUC).

Implications of our behavioral data for gambling behavior

Our present experiment has two important points for an understanding of gambling behavior: (i), factors in self-reported impulsivity (i.e., attentional impulsiveness and a thrill and adventure seeking tendency) were strongly associated with preference for uncertain rewards, and (ii) there was a negative relationship between probability discounting of gains and losses. The first point is consistent with our intuition. The second point is also important in that this indicates that subjects who prefer large uncertain rewards to small certain ones simultaneously prefer large uncertain loss to small certain loss. In other words, subjects may be either risk-seeking (or risk–aversive) in both gain and loss domains ("risk" refers to uncertainty in the acquisition of rewards and potential loss here). Based on these current findings, we propose that discounting frameworks may be useful for a better understanding of deficits in the IGT (Iowa gambling task), which is the most standard laboratory experimental task for investigating gambling behavior.

2. Discounting theory and the Iowa gambling task (IGT)

As noted above, Rachlin's probability discounting theory can be best applied to a repeated gambling paradigm such as the Iowa gambling task (IGT). In the probability discounting theory, a devaluation of uncertain outcomes corresponds to delay discounting of uncertain outcomes in repeated gambles. Therefore, "foresight" and "future myopia" in probability discounting in Rachlin's sense is well defined in relation to delay discounting. In order to apply probability discounting theory to the IGT, we should more closely look at outcomes (rewards and punishments) and their associated probabilities for the four decks in the IGT.

Among several variants in the versions of the IGT, in this study we focus on the original version of the IGT employed in Bechara et al (2000), (i.e., the "ABCD" version). In this version of the IGT, subjects are required to choose between four decks A, B, C, and D. Each deck is associated with a (regular and certain) positive outcome (a reward) and uncertain negative outcomes (probabilistic punishments). We indicate the probability of each uncertain punishment with the magnitude of A_{loss} (dollars) by $p_{loss}(A_{loss})$ associated with each deck; while the amount of the regular (i.e., certain) rewards by A_{gain} (dollars). It is to be noted that in this version of the IGT, there is no uncertainty in the gain domain (i.e., $p_{gain}(A_{gain})=1$ for all decks). For deck A and B, A_{gain}=\$100; while for deck C and D, A_{gain}=\$50. The punishments associated with the decks are more complicated. Deck A is associated with five uncertain losses of which magnitudes were \$150, \$300, \$200, \$250, and \$350, with the same probabilities=0.1; namely, $p(A_{loss}=150)=p(A_{loss}=300)=p(A_{loss}=200)=p(A_{loss}=250)= p(A_{loss}=350)=0.1$. Deck B is associated with a large uncertain punishment of \$1250 of which probability is $p(A_{loss}=1250)=0.1$. Deck C is associated with three uncertain punishments: \$50, \$25, and \$75 of which probabilities are $p(A_{loss}=50)=0.25$, $p(A_{loss}=25)=0.125$, and $p(A_{loss}=75)=0.125$, respectively. Finally, Deck D is associated with an uncertain punishment of \$250 with the probability of $p(A_{loss}=250)=0.1$. It is important to note that the good decks are deck C and D (providing a mean return of \$25>0; rewarding in a long run); while bad decks are deck A and B (providing a mean return of - \$25, i.e., an average, long-run outcome is a loss). As noted above, several psychiatric/neurological patients prefer the bad decks (A and B) to the good decks (C and D); while healthy controls prefer the good decks (C and D) to the bad decks (A and B) (Bechara et al., 1994; 2000; 2002).

Because we propose that decision in the IGT is determined by probability discounting, it is necessary to compute the values of all decks A-B based on the probability-discounting function (Equation 2). We show an instance of a procedure to perform this calculation for deck A alone, in order to avoid showing long simple calculations.

For deck A, $V_{p\_gain}(A_{gain}=100)=\$100$ (no probability discounting for gains) (Bechara et al., 1994; 2000; 2002). The total value of the uncertain punishments associated with deck A is:
$150/[1+k_p(1/0.1-1)]+300/[1+k_p(1/0.1-1)]+200/[1+k_p(1/0.1-1)]+250/[1+k_p(1/0.1-1)]+350/[1+k_p(1/0.1-1)]=1250/(1+9k_p)$. Note that k_p is a hyperbolic probability discounting rate defined in equation 4. Therefore, the total (probability-discounted) value of deck A =V(A) is [(value of gain of deck A)-(value of punishments of deck A)]=$100-1250/(1+9k_p)$. After similar calculations, we obtain, $V(B)=100-1250/(1+9k_p)$, $V(C)=50-[50/(1+3k_p)+100/(1+7k_p)]$, and $V(D)=50-250/(1+9k_p)$, where V(x) indicates the value of deck x (x=A, B, C, D) [1]. Therefore, the value of "bad decks" is [V(A)+V(B)]/2; while the value of "good decks" is [V(C)+V(D)]/2 (these quantities can now be explicitly expressed in terms of k_p, a future myopia parameter in probability discounting).

We should next explore the condition for advantageous performance in the IGT (preference for "good decks" over "bad decks"); i.e, $[V(A)+V(B)]/2 < [V(C)+V(D)]/2$. After numerically solving this inequality, we obtain $(0<)k_p<2.082$ (approximately 2.1) as a condition for preference for good decks over bad decks (i.e., advantageous performance in the Iowa gambling task). It is important to again note that k_p indicates the degree of "future myopia in probability discounting" (i.e., large k_p indicates insensitivity to future consequences of repeated gambling) and k_p is not strongly associated with k_D in a delay discounting task (in equation 2) (Ohmura et al., 2005). Previous studies observed that healthy (control) subject's k_p (the degree of future myopia in probability discounting) is approximately 1-1.5 < 2.1 (Reynolds et al., 2004; Ohmura et al., 2005). Therefore, the present hypothesis that decision in the IGT is determined by "future myopia in probability discounting"($=k_p$), successfully explains healthy control subject's ability to choose advantageous decks (i.e., deck C, D) in the IGT.

Let us now see numerical examples predicted from our hypothesis. The values of decks A and B are: V(A)=\$13.8, V(B)=\$13.8, V(C)=\$32.2, and V(D)=\$32.8, when $k_p=1.5$ (a typical k_p value in healthy subjects (Reynolds et al., 2004; Ohmura et al., 2005)). This indicates that good decks are much more valuable than bad decks, for typical healthy subjects. When $k_p=1$, V(A)=V(B)= –\$25 (<0) and V(C)=V(D)=+\$25, consistent with the aforementioned mathematical characteristic of the present framework: a subjective value of an uncertain outcome in hyperbolic probability-discounting equals a statistical expected value when $k_p=1$ (also confirming the validity of our calculations of values of the decks). On the contrary, when $k_p=2.5$ (>2.1, a high degree of "future myopia in probability discounting" in Rachlin's sense), V(A)=V(B)=\$46.8, V(C)=\$32.1, and V(D)=\$39.4. This demonstrates that deck A and B ("bad decks") are more preferred than deck C and D ("good decks") by subjects with a high degree of future myopia in probability discounting (i.e., $k_p>2.1$). The additional important point here is that V(A)=V(B)>0 (perceived as *gains* rather than *losses* by subjects) when $k_p>1.28$, although long-term (mean) returns from these decks are negative (=–\$25).

Finally, it should be noted that the rate of probability discounting of loss is a more appropriate predictor of performance in IGT, since the essential distinction between good and bad decks exists in potential punishments. Therefore, future studies should examine the relationship between performance in the IGT and probability discounting of loss, rather than probability discounting of gain. Furthermore, a recent study demonstrated that control subjects had more strong "myopic loss aversion" than ventromedial patients (Shiv et al., 2005). Future studies should examine the neuropsychological processes underlying myopic loss aversion, by utilizing delay and probability discounting framework.

3. Conclusions

In this study, we propose that the discounting theory (especially a parameter of probability discounting of loss) may be useful for a neuroeconomic understanding of pathological gambling. The reason is that pathological gambling is characterized by insensitivity to potential bad consequences in the long-run. In this theoretical framework, "future myopia" in the somatic marker hypothesis is well defined by Rachlin's theoretical equivalence of delay and probabilistic uncertainty. Furthermore, we observed that factors in self-reported impulsivity scales were associated with preference for large but uncertain outcomes. Hence, self-reported impulsivity is also an important determinant of gambling behavior, since reward from gambling is large but uncertain. Future studies should examine neuropsychological processing underlying probability discounting of loss, in order to elucidate risky gambling behavior. An assessment of probability discounting of loss by ventromedial patients and pathological gamblers may be helpful.

Ainslie G (2005) Précis of Breakdown of Will. *Behavioral and Brain Science.* 28(5):635-650.

Alessi SM, Petry NM. (2003) Pathological gambling severity is associated with impulsivity in a delay discounting procedure. *Behavioral Processes.* 64(3):345-354.

Bechara A, Damasio AR, Damasio H, Anderson SW. (1994) Insensitivity to future consequences following damage to human prefrontal cortex. *Cognition.*50(1-3):7-15.

Bechara A, Tranel D, Damasio H. (2000) Characterization of the decision-making deficit of patients with ventromedial prefrontal cortex lesions. *Brain.* 123 (Pt 11):2189-2202.

Bechara A, Dolan S, Hindes A. (2002) Decision-making and addiction (part II): myopia for the future or hypersensitivity to reward? *Neuropsychologia.* 40(10):1690-1705.

Berlin HA, Rolls ET, Kischka U. (2004) Impulsivity, time perception, emotion and reinforcement sensitivity in patients with orbitofrontal cortex lesions. *Brain.* 127(Pt 5):1108-1126.

Bickel WK, Marsch LA (2001) Toward a behavioral economic understanding of drug dependence: delay discounting processes. *Addiction.* 96, 73-86.

Bickel WK, Miller ML, Yi R, Kowal BP, Lindquist DM, Pitcock JA. (2006) Behavioral and neuroeconomics of drug addiction: competing neural systems and temporal discounting processes. *Drug and Alcohol Dependence.* 2 Suppl 1:S85-91.

Chiu YC, Lin CH.(2007) Is deck C an advantageous deck in the Iowa Gambling Task? *Behavioral and Brain Functions.* 3:37.

Clark L, Cools R, Robbins TW (2004) The neuropsychology of ventral prefrontal cortex: Decision-amking and reversal learning. *Brain and Cognition*, 55, 41-53.

Crean JP, de Wit H, Richards JB. (2002) Reward discounting as a measure of impulsive behavior in a psychiatric outpatient population. *Experimental & Clinical Psychopharmacology.* 8(2):155-162.

Damasio AR (1994) *Descartes error: Emotion, reason and the human brain.* New York: Grosset/Putnam.

Damasio AR (1996) The somatic marker hypothesis and the possible functions of the prefrontal cortex. *Philos Trans R Soc Lond B Biol Sci.* 351(1346):1413-1420.

Daruna JH, Barnes PA (1993) A neurodevelopmental view of impulsivity. In: McCown WG, Johnson JL, Shure MB (eds) The impulsive client: theory research and treatment. American Psychological Association, Washington, DC, pp 23–37.

Dixon MR, Marley J, Jacobs EA. (2003) Delay discounting by pathological gamblers. *Journal of Applied Behavioral Analysis.* 36(4):449-458.

Dom G, De Wilde B, Hulstijn W, Sabbe B. (2007) Dimensions of impulsive behaviour in abstinent alcoholics. *Personality and Individual Differences 42* 465–476.

Dunn BD, Dalgleish T, Lawrence AD. (2006) The somatic marker hypothesis: a critical evaluation. Neuroscience & Biobehavioral Review. 30(2):239-271.

Fellows LK. (2004) The cognitive neuroscience of human decision making: a review and conceptual framework. *Behavioral and Cognitive Neuroscience Review.* 3 159-172.

Fukui H, Murai T, Fukuyama H, Hayashi T, Hanakawa T. (2005) Functional activity related to risk anticipation during performance of the Iowa Gambling Task. *Neuroimage.* 24:253-259.

Harmsen H, Bischof G, Brooks A, Hohagen F, Rumpf HJ. (2006) The relationship between impaired decision-making, sensation seeking and readiness to change in cigarette smokers. *Addictive Behaviors.* 31(4):581-592.

Holt DD, Green L, Myerson J (2003) Is discounting impulsive? Evidence from temporal and probability discounting in gambling and non-gambling college students. *Behavioural Processes* 64 (3): 355-367.

Kalidindi K, Bowman H. (2007) Using -greedy reinforcement learning methods to further understand ventromedial prefrontal patients' deficits on the Iowa Gambling Task. *Neural Networks*. 20(6):676-689.

Kirby KN, Petry NM, Bickel WK.(1999) Heroin addicts have higher discount rates for delayed rewards than non-drug-using controls. *Journal of Experimental Psychology General.*128(1):78-87.

Lagorio CH, Madden GJ (2005) Delay discounting of real and hypothetical rewards III: Steady-state assessments, forced-choice trials, and all real rewards. *Behavioural Processes* 69 (2): 173-187 Sp. Iss. SI

Lakey CE, Goodie AS, Lance CE, Stinchfield R, Winters KC.(2007) Examining DSM-IV criteria for pathological gambling: psychometric properties and evidence from cognitive biases. *Journal of Gambling Studies.* 23(4):479-498.

Lin CH, Chiu YC, Lee PL, Hsieh JC. (2007) Is deck B a disadvantageous deck in the Iowa Gambling Task? *Behavioral and Brain* Functions. 3:16.

MacKillop J, Anderson EJ, Castelda BA, Mattson RE, Donovick PJ. (2006) Divergent validity of measures of cognitive distortions, impulsivity, and time perspective in pathological gambling. *Journal of Gambling Studies.* 22(3):339-354.

Madden GJ, Begotka AM, Raiff BR, Kastern LL (2003) Delay discounting of real and hypothetical rewards. *Experimental & Clinical Psychopharmacology* 11 (2): 139-145.

Madden GJ, Raiff BR, Lagorio CH, Begotka AM, Mueller AM, Hehli DJ, Wegener AA (2004) Delay discounting of potentially real and hypothetical rewards: II. Between- and within-subject comparisons. *Experimental & Clinical Psychopharmacology.* 12 (4): 251-261.

Mazur JE (1987) An adjusting procedure for studying delayed reinforcement. In: Commons ML, Mazur JE, Nevin JA, Rachlin H (eds) Quantitative analysis of behavior, vol 5. The effects of delay and of intervening events on reinforcement value. Erlbaum, Hillsdale, NJ, pp 55–73.

Monterosso J, Ehrman R, Napier KL, O'Brien CP, Childress AR. Three decision-making tasks in cocaine-dependent patients: do they measure the same construct? *Addiction*, 96 (2001): 1825-1837.

Myerson J, Green L, Warusawitharana M (2001) Area under the curve as a measure of discounting. *Journal of Experimental Analysis of Behavior* 76:235–243.

Ohmura Y, Takahashi T, Kitamura N. Discounting delayed and probabilistic monetary gains and losses by smokers of cigarettes. *Psychopharmacology (Berl).* 2005 182: 508-515.

Ohmura Y, Takahashi T, Kitamura N, & Wehr P (2006). Three-month stability of delay and probability discounting measures. *Experimental and Clinical Psychopharmacology*, 14: 318-328.

Passetti F, Clark L, Mehta MA, Joyce E, King M. (2007) Neuropsychological predictors of clinical outcome in opiate addiction. *Drug and Alcohol Dependence*. (in press)

Patton, J. H., Stanford, M. S. & Barratt E. S. (1995). Factor structure of the barratt impulsiveness scale. *Journal of Clinical Psychology* 51: 768-774.

Petry NM (2001a) Pathological gamblers, with and without substance use disorders, discount delayed rewards at high rates. *Journal of Abnormal Psychology.* 110(3):482-487.

Petry, N. M (2001b) Delay discounting of money and alcohol in actively using alcoholics, currently abstinent alcoholics, and controls. *Psychopharmacology, 154,* 243-250.

Rachlin H, Raineri A, Cross D. Subjective probability and delay. *J Exp Anal Behav.* 1991 55:233-244.

Reynolds, B., Richards, J. B., Horn, K., & Karraker, K. Delay discounting and probability discounting as related to cigarette smoking status in adults. *Behavioral Processes, 65* (2004) 35-42.

Richards JB, Zhang L, Mitchell SH, de Wit H. (1999) Delay or probability discounting in a model of impulsive behavior: effect of alcohol. *Journal of Experimental*

Analysis of Behavior. 71(2):121-143.

Samuelson, PA. A note on measurement of utility. (1937) *The Review of Economic Studies,* 4(2): 155-161.

Sanfey AG, Hastie R, Colvin MK Grafman J (2003) Phineas gauged: Decision-making and the frontal lobes. *Neuropsychologia*, 41, 1218-1229.

Shiv B, Loewenstein G, Bechara A. (2005) The dark side of emotion in decision-making: when individuals with decreased emotional reactions make more advantageous decisions. *Brain Research- Cognitive Brain Research.* 23(1):85-92.

Simpson CA, Vuchinich RE (2000) Reliability of a measure of temporal discounting. *Psychological Record* 50:3–16.

Sloman, A (2004) What are emotion theories about? In Invited talk at cross-disciplinary workshop on architectures for modeling emotion at the AAAI spring symposium at Stanford University in March 2004

Someya, T., Sakado, K., Seki, T., Kojima, M., Reist, C., Tang, S.W. & Takahashi S. (2001). The Japanese version of the Barratt Impulsiveness Scale, 11th version (BIS-11): its reliability and validity Psychiatry and Clinical Neurosciences 55: 111-114.

Takahashi T. (2005) Loss of self-control in intertemporal choice may be attributable to logarithmic time-perception. *Medical Hypotheses* 65(4):691-693.

Takahashi T. (2004) Cortisol levels and time-discounting of monetary gain in humans. *Neuroreport.* 15(13):2145-2147.

Takahashi T, Ikeda K, Fukushima H, Hasegawa T. (2007) Salivary alpha-amylase levels and hyperbolic discounting in male humans. *NeuroEndocrinology Letters.* 28(1):17-20.

Terasaki M, Shiomi K, Kishimoto Y, Hiraoka K (1987) A Japanese version of the sensation seeking scale. *Japanese Journal of Psychology* 58 (1): 42-48.

Toplak ME, Jain U, Tannock R. (2005) Executive and motivational processes in adolescents with Attention-Deficit-Hyperactivity Disorder (ADHD). *Behavioral and Brain Functions*. 27;1(1):8.

van Honk J, Hermans EJ, Putman P, Montagne B, Schutter DJ.(2002) Defective somatic markers in sub-clinical psychopathy. *Neuroreport.* 13(8):1025-1027.

Verdejo-García A, Rivas-Pérez C, Vilar-López R, Pérez-García M. Strategic self-regulation, decision-making and emotion processing in poly-substance abusers in their first year of abstinence. *Drug and Alcohol Dependence*. 86(2-3):139-146.

Zuckerman, M. & Neeb, M. (1979). Sensation seeking and psychopathology. Psychiatry Research 1: 255-264.

Zuckerman, M (1971) Dimensions of sensation seeking. Journal of consulting and clinical psychology. 36:45.

Table 1 Correlation between self-reported impulsivity and AUCs of discounting.

		BIS	SSS
Delay Discounting			
	Gain	-0.23 †	-0.09
	Loss	-0.34 *	-0.10
Probability Discounting			
	Gain	0.19	0.28 *
	Loss	-0.21	-0.08

Note that a negative (positive) correlation between AUC and scales indicates a positive (negative) correlation, because smaller AUC values correspond to stronger discounting. * $p < .05$ † $p < .10$

Table 2. Correlation between factors in BIS and AUCs of discounting.

	BIS	AI	MI	NI
Delay Discounting				
Gain	-0.23 †	-0.03	-0.25 †	-0.28 *
Loss	-0.34 *	-0.11	-0.33 *	-0.30 *
Probability Discounting				
Gain	0.19	0.30 *	0.04	0.11
Loss	-0.21	-0.23 †	-0.05	-0.23 †

Note that a negative (positive) correlation between AUC and scales indicates a positive (negative) correlation, because smaller AUC values correspond to stronger discounting. * $p < .05$ † $p < .10$

Table 3. Correlation between factors in BIS and AUCs of discounting.

	SSS	TAS	ES	Dis	BS
Delay Discounting					
Gain	-0.09	-0.02	-0.08	-0.17	-0.16
Loss	-0.10	-0.07	-0.14	-0.13	0.03
Probability Discounting					
Gain	0.28 *	0.29 *	0.20	0.15	0.04
Loss	-0.10	-0.08	0.01	-0.09	-0.02

Note that a negative (positive) correlation between AUC and scales indicates a positive (negative) correlation, because smaller AUC values correspond to stronger discounting. * $p < .05$ † $p < .10$

Modeling Decision Mechanism as a Reinforcement Learning with Probabilistic Discounting

Takaki Makino [1) 3)], Taiki Takahashi [2)], Hiroki Fukui [3)]
1) Division of Project Coordination, University of Tokyo
2) Department of Behavioral Science, Hokkaido University
3) Department of Forensic Psychiatry, National Center of Neurology and Psychiatry

1. Introduction

Iowa Gambling Task (IGT) [1,2] is a behavioral experiment task that investigates action selection under an environment with probabilistic outcome. It is known that patients with lesions on ventromedial prefrontal cortex (VMPFC) and amygdala tend to show impaired action selection, that is, failure in learning to select beneficial actions and continue choosing non-beneficial actions. These brain areas are associated with Somatic Marker hypothesis [5] (the function to learn outcome of actions through emotional reactions), and the impairment of action selection has been attributed to the damage of Somatic Marker functions. Thus, the valence model was widely used to analyze the result of IGT tasks, which is parameterized by the weight w between positive and negative stimulus. However, the impairment of action selection by VMPFC-lesioned patients may come from the myopic behavior of the patients, making larger discount on temporally distant results [6]. Since IGT has temporally unchanging structure, we cannot directly test myopicity; but if we use a behavioral model based on Rachlin's probabilistic discounting theory [3], that describes correlation between probabilistic discounting and temporal discounting, we can make an indirect analysis of myopicity on the result of IGT.

In this study, we compared the estimated parameters by the existing valence model and proposed probability discounting model on the set of IGT behavioral data, which include both the original IGT and variant IGT (with inversed penalties and rewards) for healthy subjects and VMPFC-lesioned patients.

2. Iowa Gambling Task

In Iowa Gambling Task (IGT), the subject repeatedly chooses one card deck out of four. The subject gains some virtual money, whose amount is fixed for each deck. After that, the subject may lose some money, whose amount and probability also depend on the chosen deck. The goal of the task is to increase the virtual money as much as possible, starting with $2,000 through the game.

Two of the four decks (A and B) have assigned a large fixed gain $100 with large loss so that the mean benefit from the decks is negative, while the other two (C and D) have assigned a small fixed gain $40 and smaller loss so that the mean benefit from the decks is positive.

It is known that healthy subjects are tend to choose good decks (C and D) in the long run, unlike the patients with lesions on ventromedial prefrontal cortex (VMPFC) or amygdala, who tend to choose bad decks (A and B). It is said that the lesions on these brain regions causes deficit in somatic marker, which plays an important role in learning against large penalty.

In this study, we performed experiments with the variant version of IGT as well as original IGT. The variant IGT has the reversed setting, that is, fixed loss and probabilistic gain.

IGT Original Task

	A	B	C	D
a. Fixed gain	$100	$100	$50	$50
b. Loss probability	50%	10%	50%	10%
c. Average loss value	- $250	- $1250	- $50	- $250
d. Mean Benefit (a+bc)	- $25	- $25	+ $25	+ $25

IGT Variant Task

	E	F	G	H
a. Fixed loss	- $100	- $50	- $100	- $50
b. Gain probability	10%	50%	50%	10%
c. Average gain value	$1250	$50	$250	$250
d. Mean benefit (a+bc)	+ $25	- $25	+ $25	- $25

Figure 1. Iowa Gambling Task

3. Data Analysis with RL Models

In this study, we analyzed the behavioral data with reinforcement learning-based models to extract the characteristics of the subjects' choice. In the theory of reinforcement learning, the choice of action is considered as a decision process based on the (subjective) values of actions, and the values are decided from the past experience of the choice of action and its result. We can model this process using a pair of a value judgment model and an action selection model.

In this study, we compared two value judgment models in terms of most likely parameters. The parameters of models for each subject are calculated so that the probability distribution of action selection predicted by the model give the maximum likelihood for the actual action selections taken by the subject. As for action selection model, we adopt Soft-max model, which gives the probability $P_t(a)$ of selecting action a at time t, using the estimated value $V_t(a)$ of choosing deck a at time t and reverse temperature β (corresponding to the consistency of action selection):

$$P_t(a) = \frac{e^{\beta V_t(a)}}{\sum_{a'} e^{\beta V_t(a')}}$$

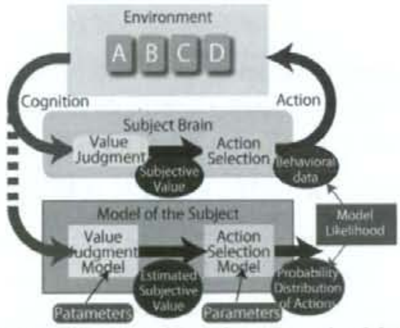

Figure 2. Diagram of Reinforce Learning Models

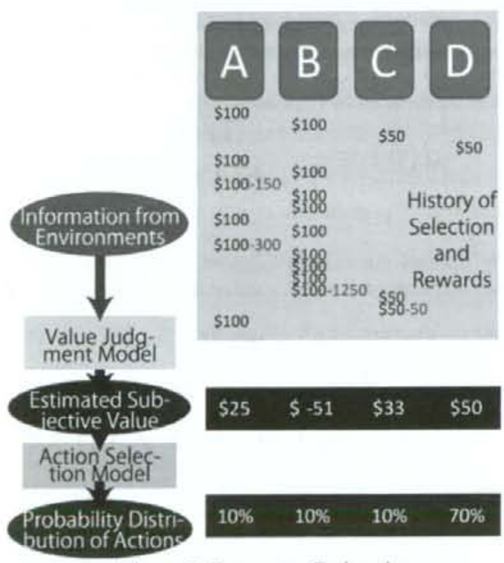

Figure 3. Parameter Estimation

4. Data and Models

In this study, we compared parameter distributions for healthy and VMPFC-lesioned subjects between existing valence model and proposed probability-discounting model. To exclude inaccurate parameter values caused by bad fitting, we used the parameter values only when the Akaike Information Criterion of the model for a subject is above the baseline (uniform distribution model).

	# subjects	Fit for probability-discount model	Fit for valence model
Healthy	38	25	29
Original	20	18	18
Variant	18	9	13
VMPFC	12	8	9
Original	10	7	8
Variant	2	1	1

4.1. Existing Method: Valence model

In Valence Model, the estimated value is updated based on the following formula.

$$V_t(a) = V_{t-1}(a) + \gamma[r_t(a) - V_{t-1}(a)]$$
$$r_t(a) = w \cdot r_t^+(a) + (1-w) \cdot r_t^-(a)$$

where γ($0 \leqq \gamma \leqq 1$) is the parameter for update speed (larger γ makes the estimation closer to the outcome of the last action r_t and ignores older outcomes), and w ($0 \leqq w \leqq 1$) is the weighting parameter between positive outcome r_t^+ and negative outcome r_t^- (larger w overweights positive outcome.)

4.2. Proposed Method: Probability-Discounting model

In probability discounting model [3], an event with probability p is cognitively processed through the average waiting time, that is, the expected number of trials until the next occurrence of the event ($1/p - 1$). Such a model can deal with "myopic" subjects, who tend to discount events with large average waiting time. Such a discounting can be modeled by hyperbolic delay discounting using parameter h:

$$d(p) = \frac{1/p}{1 + h(1/p - 1)}$$

When h>1, the model tend to neglect probabilistic events; when h<1, the model tend to be sensitive for probabilistic events.

Our model independently updates the value V^S of certain outcomes and value V^P of probabilistic outcomes, and calculates the final estimated value V using the estimated probability $p_t(a)$ of probabilistic outcomes.

$$V_t^S(a) = V_{t-1}^S(a) + \gamma[r_t^S(a) - V_{t-1}^S(a)]$$
$$V_t^P(a) = V_{t-1}^P(a) + \gamma[r_t^P(a) - V_{t-1}^P(a)]$$
$$V_t(a) = V_t^S(a) + d(p_t(a)) \cdot V_t^P(a)$$

5. Results and Discussions

Figures 4 and 5 show the distribution of parameters for the model-fit cases. In existing valence model, the estimated parameter w showed no significant difference between healthy subject group and VMPFC-lesioned patient group. On the other hand, using the proposed probability discounting model, we found significant different (p<.05) of discounting parameter h between healthy and VMPFC-lesioned