Role of Affect and Risk-Benefit Perception on Reckless Betting: Prior Wins and Losses Both Lead to Risky Bets

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Abstract

People who have experienced many gambling wins tend to make larger bets even when they are unlikely to win (*reckless betting*) than those who have experienced many losses. This study examined psychological factors underlying reckless betting when gambling from the perspectives of affect and risk-benefit perception. University students (N = 63) participated in an experiment using the Acey-Deucey Task, in which the number of wins and losses during the 1st session was experimentally manipulated such that there were either 24, 12, or 6 wins out of 30 trials. Positive-negative affect and perceived risk-benefit during the task were assessed by self-report. Betting recklessness during the 2nd session was calculated using winning probability and bet size data in each trial. The results indicated that experiencing few prior wins, that is, many prior losses decreased positive affect and perceived benefits of betting and increased negative affect and perceived risks of betting. Path analysis results suggested that gambler's positive and negative affect altered perceived benefits of betting, which influenced reckless betting. Although participants that experienced more prior wins made more reckless bets similar to previous studies, there were no statistical differences between the three groups. Time-series analysis revealed that participants who experienced many prior losses made increasingly reckless bets at the end of the gambling task. We have discussed other potential variables that might have influenced recklessness, and the time-series analysis' implications on reckless betting and loss-chasing.

Keywords: reckless betting; affect; risk-benefit perception; time-series analysis; loss-chasing

Declarations

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Conflicts of Interest

Authors have no conflicts of interest to disclosure that are relevant to the content of this article.

Availability of Data, Code and Material

Dataset and analysis codes used in this study are available at https://osf.io/548fg/?view_only=75b685d2490b4a1e8d4078fb3a4f48a1. The corresponding author can provide experimental materials, including the PsychoPy program for the Acey-Deucey task (in Japanese), upon request.

Authors' Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Daiki Taoka. The first draft of the manuscript was written by Daiki Taoka, and Takashi Kusumi commented on previous versions of the manuscript for revision. All authors read and approved the final manuscript.

Ethics Approval

The experiment was conducted after obtaining the ethical approval of the ethics committee of the Graduate School of Education of Kyoto University (Date: 2019/6/14; Ethics approval number: CPE-307).

Consent to Participate

Written informed consent to participate was obtained from all the participants before and after the experiment. None of the participants withdrew their consent to participate.

Consent for Publication

Written consent for publication of research results was obtained from all participants before and after the experiment. None of the participants withdrew their consent for publication.

Gambling is to bet money or other things of value on the results of uncertain events at the risk of losing them in return for a chance of obtaining more benefit. People make bets on horse racing, card games, lotteries, and slot machines (see Calado et al., 2017 for an international review and Hayano et al., 2021 for a recent survey in Japan). Gamblers exhibit different types of irrational behaviors that are not explicable from a rational or an economic perspective (Delfabbro, 2004; Fortune & Goodie, 2012; Ladouceur & Walker, 1996). Reckless betting is one type of irrational betting behavior in which people bet too much even though they are more likely to lose than win (Cummins et al., 2009). For example, B is more reckless when comparing two bets on a game with a 30% chance of winning, such that A is a 100-chip bet and B is a 200-chip bet. Similarly, betting on gamble D would be more reckless when considering a 100-chip bet on two gambles with different winning chances, such that C has a 30% and D has a 20% winning chance. In other words, reckless betting is trying to gain more by taking risks in a gamble with negative economic utility.

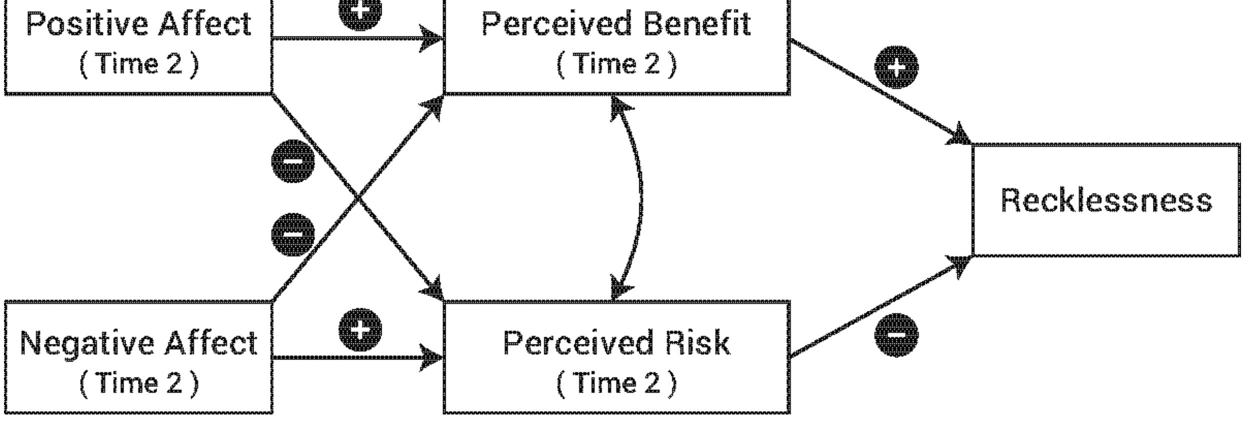
Cummins et al. (2009) determined the Expected Chips Lost (ECL) as an index of betting recklessness by considering the above operational definition. The ECL is calculated based on the value of a bet placed on a gamble (i.e., bet size) when the objective winning probability is less than 50%. Cummins et al. (2009) conducted experiments using a gambling task and examined the effects of prior winning versus losing experiences on subsequent betting recklessness. Their results indicated that participants experiencing many wins in the first session of the task made more reckless bets in the second session than those who experienced many losses in the first session. In their experiment, the participants' chip totals were reset at the beginning of the second session, and all participants started with the same number of chips. Therefore, the *house money effect*

(Thaler & Johnson, 1990) could not explain these results, and so, Cummins et al. (2009) argued that prior winning experiences facilitated reckless betting. In Japan, the identical result was reported in a study using a different gambling task. Takada and Yukawa (2012) demonstrated that participants experiencing wins in an immediately preceding single trial or consecutive two trials tended to make reckless choices in the next trial than those who experienced losses in immediately preceding trials. More recently, Taoka and Ariga (2019), using a similar experimental paradigm as Cummins et al. (2009), reported that the effect of prior winning experiences on subsequent reckless betting was robust even if people could freely quit betting which is the case in real gambling. These two studies together show that prior winning experiences could be crucial for facilitating reckless betting.

Previous studies have also focused on psychological factors associated with reckless betting, including positive and negative affect during gambling. Cummins et al. (2009) indicated that positive affect significantly increased after winning experiences than after losing experiences, and recklessness of subsequent bets was positively correlated with positive affect ($r = .29$). Based on the results, the researchers speculated that prior experience of many wins leads to higher positive affect, which in turn results in more optimistic risk perceptions. Positive affect might also cause reckless betting through underestimation of risks. However, the hypotheses developed by Cummins et al. (2009) have not been examined to date, although specific risk perception studies have provided supporting evidence. For example, Haase and Silbereisen (2011) found that perceived risk was reduced when positive affect was induced. On the other hand, Sobkow, Traczyk, and Zaleskiewicz (2016) reported that negative affect evoked by mental imaginary of risk consequences increased perceived risks. Many studies on probability judgments have argued that the estimated probability of desirable events is higher when positive affect is induced in risky situations (e.g., Johnson & Tversky, 1983; Nygren et al., 1996; Wright & Bower, 1992). It can be expected that a higher subjective probability of desired events would lead to overestimation of betting benefits (i.e., wins and gains) and underestimation of betting risks (i.e., losses). Research in another context has argued that the affect induced by a risk judgment target plays an essential role in risk-benefit perception. Slovic et al. (2007) suggested that the affect induced by a target is a conscious or an unconscious marker indicating the "goodness" or "badness" of the target, which is used for decision making and judgments (affect heuristic). Risks are perceived as low, and benefits are perceived as high when referring to positive affect, whereas risks are perceived as high, and benefits are perceived as low when referring to negative affect. Therefore, empirical evidence from different directions has demonstrated that affect influences risk-benefit

Fig.1

Hypothesized path model of relationships among positive and negative affect, perceived risk-benefit, and recklessness. The variables enclosed in squares are the variables to be measured. The sign attached to the path represents the direction of the effect. For example, the path between “Positive Affect” and “Perceived Benefit” denotes a positive effect: the higher was the positive affect, the higher was the perceived benefit.



perception. Thus, people would make larger bets even when they are unlikely to win because affect causes them to overestimate benefits or underestimate risks. We assumed that a similar mechanism underlies reckless betting, as illustrated in Fig. 1.

Significantly, "affect" in these studies does not refer to a specific *emotion* such as fear or anger that motivates people to respond immediately to a particular event (Lerner & Keltner, 2000), but rather to an ambiguous *mood* or *valenced feeling* that people experience when facing the target of a risk-benefit judgment (Slovic & Peters, 2006). Previous research on reckless betting has not always made a clear distinction between these concepts of emotions. However, we use the term "affect" to describe moods and feelings with a positive or negative valence in this paper. Moods and feelings can go up and down over a series of gambling trials; gambling outcomes would change the mood and alter feelings regarding the target object. If affect influences gambling-related cognitive processes that lead to reckless betting, including risk perceptions and probability judgments, this effect might be expected to persist for an extended period or decrease gradually. For example, a gambler who has experienced many prior wins and induced a positive affect might experience a decrease in positive affect and an increase in negative affect if he or she continues to lose on subsequent gambles. Therefore, it is necessary to examine the persistent effect of prior winning experiences on recklessness, and whether recklessness changes with affect.

However, it is challenging to continuously assess affect during a gambling task because frequently self-reporting during a gambling task might cause participants to deviate from the original task. Frequently self-reporting might also alter the influence of affect on participants' betting behavior by making them aware of their affective states. In addition, we were concerned about affect assessment methodology because recent literature on affect assessment indicates no consensus on procedures for assessing within-person affect variations over time (Brose et al., 2020). Brose et al. (2020) pointed out that the conventional use of existing affect assessment instruments (e.g., PANAS; Watson et al., 1988) might be inappropriate for intensive longitudinal assessments. Therefore, we examined time-series changes in recklessness in the first step, considering trial data on a gambling task as time-series data. The hypothesis that affective states influence reckless betting would be supported if there were a correspondence between within-session time-series changes in recklessness and pre- and post-session affective states.

Examining within-session changes in recklessness is meaningful because they might identify relationships between reckless betting and within-session loss-chasing, or continuing to bet and increasing bet sizes to recoup previous losses (for a recent review, Zhang & Clark, 2020). O'Connor and Dickerson (2003) identified "continuing to gamble and increasing bet sizes" as a general feature of within-session loss-chasing. Indeed, increasing the bet size is an essential common feature of reckless betting and loss-chasing, suggesting a close link between them. However, there is no evidence of this association to date because previous studies have assessed recklessness by aggregating participants' behavioral data across sessions, which might have overlooked information on time-series changes in recklessness.

This study was intended to increase our understanding of psychological mechanisms of reckless betting. There were two purposes for this study based on the above-discussed perspectives. The first purpose was to examine the effects of positive-negative affect and risk-benefit perception during a gambling task on recklessness by assessing them at multiple time points and examining their changes in winning versus losing scenarios. We predicted that winning scenarios' positive affect and perceived benefits would increase, whereas negative affect and perceived risks would decrease (and vice versa in the losing scenarios). We also examined relationships between affect and risk-benefit perception on recklessness through path analysis of the hypothetical model in Fig. 1. The second purpose was to investigate the within-session time-series changes in recklessness by analyzing betting behavior data through time-series analysis. We did not develop a hypothesis on time-series changes but investigated them in an exploratory manner.

Methods

Design

The experiment had a one-factor, three-level, between-participants comparison design. The number of wins and losses during the first session of the gambling task was experimentally manipulated in three ways: winning 24 trials among 30 (winning), winning 12 trials among 30 (moderate winning), and winning 6 trials among 30 (losing).

Participants

A priori power analysis was conducted based on the highest-level effect size (Cohen's d = 1.18; 0.95) reported in previous studies using the identical experimental paradigm (Cummins et al., 2009; Taoka & Ariga, 2019), setting the significance level α at .05 and the power $1 - \beta$ at .80. We determined that we needed approximately 60 participants (20 for each group) based on the results.

We recruited 63 Japanese students from the university community (35 men and 28 women, mean age = 21.4 years, *SD* = 2.4 years) through the university co-op shop advertisements. No specific exclusion criteria were set prior to the experiment, similar to Cummins et al. (2009). The participants were randomly assigned to one of the three conditions. Among them, eight participants could not complete the 1st session of the gambling task because they lost all their chips before completing the task. Therefore, their data were excluded from the analysis because they could not receive the experimental manipulation as we intended. No participants withdrew from participating during or after the experiment. As a result, the data of 55 participants were analyzed (30 men and 25 women, mean age = 21.3 years, *SD* = 2.2 years).

Apparatus

The experimental program was controlled using PsychoPy (Peirce, 2007), free software for psychological experiments. The stimuli were presented on the 23-inch Full HD display. Participants responded using a standard keyboard with a numeric keypad. The gambling task and responding to the question items were performed using a computer and electronically recorded.

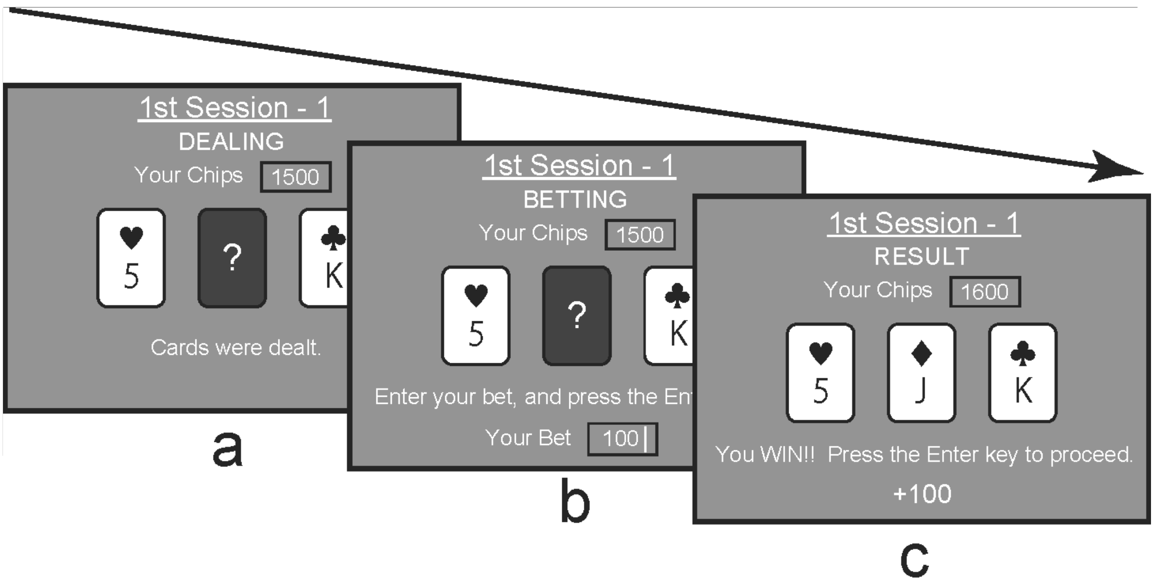
Acey-Deucey Task

The Acey-Deucey is a card game using the 52 cards of a card deck. Cummins et al. (2009) was used this game as a gambling task suitable for assessing betting recklessness. In the Acey-Deucey Task, the winning chances change from trial to trial, which can be calculated as an objective winning probability. Hence, reckless betting can be quantitatively measured in this task based on the winning probability and participants' bet size in each trial. The Acey-Deucey Task might be regarded as a simplified casino game such as poker and baccarat, in which the bet size is decided by judging the advantages or disadvantages of the situation.

Three cards were randomly selected from 52 cards and presented side by side on the screen in the Acey-Deucey Task trials. The right and left cards were presented face-up such that the numbers were visible, and the center card was presented face-down such that the number was not visible (Fig. 2a). A participant then determined bet size for the current trial by considering whether the center card would have a number in-between the left and right cards (Fig. 2b). In this task, the lowest rank card was the deuce, and the highest rank card was the ace, in the rank order, 2 < 3 < 4 < … < Q < K < A. For example, when the right and left cards were 5 and Q, the participant would win if the center card was from 6 to J, and lose if the center card was not one of those. In this example, the participant would win if any of the 24 cards (6 [numbers] × 4 [suits]) out of the remaining 50 cards fall on the center card, thus the winning probability can be calculated as 24/50 = .48. Once the bet size was determined, a message informed an outcome for the trial, and the increase or decrease of the participant's current chip number was shown on the screen. If the participant had won, they gained chips equal to the bet size, whereas if participants lost, they lost chips equal to the bet size (Fig. 2c).

Fig.2

Schematic illustration of a trial in the Acey-Deucey Task (a: Dealing phase, b: Betting phase, c: Feedback phase).



The goal of the participants in the Acey-Deucey Task was to maximize their chips through multiple trials. The participants were informed in advance that they would receive 1,000 JPY (around 10 USD) as a reward for participating in the study, which might not have been enough to motivate them to perform better in the gambling task. Therefore, we also gave the participants a results-based bonus to increase their motivation. Previous studies have used different types of bonuses to increase participants' motivation (Cummins et al., 2009; Taoka & Ariga, 2019). In this study, a results-based bonus of up to 500 JPY was provided such that participants earning many chips in the second session of the gambling task could be rewarded with 1.5 times the base reward.

We made three modifications to the procedure of Cummins et al. (2009). Firstly, we allowed participants to quit betting in the middle of the task such that they could choose before each trial to continue betting or keep their current chips by quitting and finishing the task. Taoka and Ariga (2019) also allowed participants to quit betting in the middle of the task and confirmed that consistent results could be obtained using this procedure. Secondly, we allowed a participant to place all his or her chips as the maximum bet in a single trial. This was in contrast to studies by Cummins et al. (2009) and Taoka and Ariga (2019), in which participants could only bet between 1 (minimum) and 20% of their chips (maximum) to prevent them from running out of chips and becoming unable to continue the experiment. However, a gambler can bet all the chips in real-life games such as poker and baccarat. Therefore, we decided to let participants bet all their chips as the maximum bet. The two modifications described above were adopted to make this study's task as close as possible to real-life gambling. The third modification to the procedure was increasing the maximum number of trials in the second session from 30 to 100. This was adopted to assess longer-term time-series changes in recklessness.

Measures

Manipulation Check

We requested participants to estimate the number of trials in which they won in the first session to check whether the experimental manipulation of the number of wins and losses was successful. After completion of the 1st session, participants responded to the question, "What is the percentage of winning trials in the 1st session of the task?" The answer was given as integers from 0 to 100 (%).

Positive and Negative Affect

The Japanese version of the Positive and Negative Affect Schedule (PANAS; Kawahito et al., 2011) was used to assess positive and negative affect during the task. We used PANAS because its original version (Watson et al., 1988) was used by Cummins et al. (2009). Moreover, we were not interested in specific emotions but the overall affective states. The adequate reliability and validity of the original and Japanese versions of PANAS have been confirmed. PANAS consists of 20 items comprised of two subscales; Positive Affect (PA) and Negative Affect (NA), assessed by 10 items for each subscale (e.g., PA: Strong, Enthusiastic, Proud; NA: Scared, Irritable, Distressed). Participants responded by indicating how strongly they felt the affect described in each item using a five-point Likert scale ranging from 1 (*very slightly or not at all*) to 5 (*extremely*). The measurements were conducted at three time-points during the gambling task. The two PANAS subscales had adequate internal consistency in our sample. Cronbach's alphas for the PA subscale were .89, .88, and .87 in the order of the three time-points, and those for the NA subscale were .80, .92, and .86. The sums of item scores in each subscale were calculated to obtain the PA and NA scores following Watson et al. (1988).

Perceived Risk-Benefits of betting

Perceived risks and benefits of betting were assessed using two question items: The item assessing perceived risk was, “Betting on this gambling task is risky.” The participants responded using a seven-point Likert scale ranging from 1 (*not at all*) to 7 (*extremely*). The item on perceived benefits was, “Betting on this gambling task is beneficial,” to which the participants responded using the same scale as above. The measurements were conducted at two time-points during the gambling task.

Recklessness

We operationally defined reckless betting following Cummins et al. (2009) as “to place a large bet on a trial in which it is more likely to lose than win" and used Expected Chips Lost (ECL) as an index of recklessness. To illustrate how we calculated ECL, we referred to ECL in each trial as instantaneous Expected Chips Lost (iECL) to distinguish it from ECL. The bet size (B_t) and the objective winning probability (P_t) for each Acey-Deucey trial were recorded electronically. The iECL was calculated for trials with P_t less than 0.5 (i.e., losing is more probable than winning):

$$\mathrm{iECL}_{t,i} = \begin{cases} B_{t,i} * \left(1 - P_{t,i}\right) & \text{if} \quad P_{t,i} < 0.5 \\ \mathrm{NA} & \text{if} \quad P_{t,i} \geq 0.5 \end{cases}, \tag{1}$$

where t is the trial number of the second session, and i is the participant’s ID. If P_t was greater than or equal to 0.5, iECL was regarded as a missing value for that trial because it was not included in reckless betting's operational definition. Moreover, iECL was also regarded as a missing value for trials that were not completed because the participant quitted the gambling task. The calculated values were summed up for each participant, resulting in ECL:

$$\mathrm{ECL}_i = \sum_{1}^{t} \mathrm{iECL}_{t,i} \,. \tag{2}$$

This formula shows that the lower the objective winning probability and the larger the bet size in a given trial, the higher was the calculated iECL, which was consistent with the operational definition of reckless betting.

Procedures

The participants were randomly assigned to one of three groups without their knowledge after arriving at the laboratory. Then, the experimenter described the experiment's outline and the rules of the Acey-Deucey Task to the participants; they were also instructed that the task was divided into two sessions with each session comprising 30 trials, that 1,500 chips would be given at the beginning of each session, and that they could not carry over chips obtained in the first session to the second session. Moreover, the participants were told they could quit betting in the second session if they wanted. Furthermore, participants were deceived into thinking that the cards would be randomly distributed. Next, participants were instructed that they would get a maximum bonus of 500 JPY in addition to their primary reward of 1,000 JPY, depending on the number of chips they had at the end of the second session. After the instructions, the participants conducted 10 practice trials. All participants were dealt the identical card sets in a random order, so that they would experience the same number of wins and losses during the 10 practice trials to avoid any bias among participants caused by the differences in the practice session. After the practice session, the experimenter asked if the participants had any questions and confirmed that they understood the task's rules. Then, the participants responded to the questionnaire items. Positive and negative affect and perceived risk-benefits of betting were assessed before the first session (Time 1), after which they proceeded to conduct the first session.

The first session was composed of 30 trials. Each participant received 1,500 chips at the beginning of the first session. The card sets and the outcomes of gambling (i.e., wins and losses) during the first session were predetermined depending on the group assigned to each participant: the winning group (n = 21; winning 24 trials among 30), the moderate winning group (n = 17; winning 12 trials), and the losing group (n = 17, winning 6 trials). The sequence of wins and losses was randomized. The participants responded to the manipulation check items after finishing the first session. Then, positive and negative affect and perceived risk-benefits were assessed (Time 2). Eventually, each participant's chip totals were reset to 1,500, and the second session was started.

The number of wins and losses was not manipulated, and cards were dealt randomly in the second session, including 100 trials. The participants were asked whether they wanted to continue or quit at the start of each trial, and they were allowed to quit the session whenever they wanted. If the participants chose to continue, they proceeded to the next trial, whereas if they chose to quit, the task was completed, and the number of chips they had remaining was regarded as their score. Positive and negative affect was assessed after finishing the task (Time 3).

A debriefing session was held after completing experiments, in which the study's and the experiments' purposes, and experimental manipulations in the first session were explained to the participants. After the debriefing, the participants' written consent was obtained to use the experiment's data.

Data Analysis

Statistical software R (Version 4.0.4) was used for data reduction, the calculation of descriptive statistics, and statistical hypothesis testing. First, the iECL was calculated using Equation (1), based on the objective winning probability and the bet size in each second session's trial. The iECL was linked to the trial numbers and used in the time-series analysis. The ECL was calculated using Equation (2). Additionally, the ECL_30 was calculated to compare previous studies' results and the data of the first 30 trials of the second session. Each participant's final dataset included their ID, gender, age, variables indicating the assigned group, PA and NA scores (Time 1, 2, and 3), and perceived risk-benefit (Time 1 and 2), ECL, ECL_30, and the iECL for each trial in the second session.

We conducted a time-series analysis to examine time-series changes in recklessness using iECL (i.e., recklessness measured in each trial) as time-series data, in addition to the statistical tests of the hypothesis. A smoothed trend model with second-order differencing, a time-series model type, was fitted to the iECL data. The model equation was as follows:

$$\begin{aligned} \mu_t &= 2\mu_{t-1} - \mu_{t-2} + \zeta_t, \qquad \zeta_t \sim \mathrm{Normal}\left(0, \sigma_\zeta^2\right), \\ y_{t,i} &= \mu_t + \epsilon_t, \qquad \epsilon_t \sim \mathrm{Normal}(0, \sigma_\epsilon^2). \end{aligned} \tag{3}$$

In this equation, t is the trial number, i is the participant's ID, $y_{t,i}$ is the iECL data, and parameter μ_t represents the group-level recklessness at each time-point. The ζ_t and ϵ_t represent the disturbance and the observation error term. We assumed a normal white noise with mean $\mu_\zeta = 0$ and variance σ_ζ^2 for the disturbance, and a normal distribution with mean $\mu_\epsilon = 0$ and variance σ_ϵ^2 for the observation error. The upper of Equation (3) is called the system model, which represents the time-series changes of recklessness at group level. The lower of Equation (3) is called the observation model, which assumes that individual data are generated by adding observation errors to the group-level recklessness at each time-point. This model assumes a gradual change in the degree of fluctuation between time-points. This is obvious when the system model of Equation (3) is transformed as follows:

$$\mu_t - \mu_{t-1} = \mu_{t-1} - \mu_{t-2} + \zeta_t, \qquad \zeta_t \sim \mathrm{Normal}\left(0, \sigma_\zeta^2\right). \tag{4}$$

In this equation, the amount of fluctuation from $t-1$ to t is expressed by adding the disturbance term to the amount of fluctuation from $t-2$ to $t-1$. The model contains a total of 102 parameters to be estimated: μ_1, μ_2, ..., μ_{100}, σ_ζ, and σ_ϵ, which were estimated for each group. Since we had no a priori knowledge of these parameters other than their lower bounds and rough upper bounds (i.e., from 0 to at most 100), we set a heavy-tailed student's *t* distribution with *df* = 4, μ = 0, and σ = 100, for all these parameters.

The Stan (Version 2.26.1) and the *cmdstanr* R package (Version 0.3.0), a Bayesian statistical modeling platform, were used for the time-series modeling and Bayesian parameter estimation of the model. We generated four chains of length 60,000 with a 10,000 burn-in period and obtained 200,000 random samples of the parameters by the HMC method using the Stan. We approximated the posterior distribution of the parameters by 200,000 samples. There were more than 4,000 valid samples for all parameters and generated quantities. The $\hat{R}$, Gelman-Rubin's convergence diagnostic statistics (Gelman & Rubin, 1992) were calculated for all parameters to check whether MCMC converged. The $\hat{R}$ values were less than the conventional criteria of 1.05 for all the parameters, indicating convergence across the four chains. Therefore, we concluded that the MCMC samples provide a good approximation of the parameters' posterior distribution.

The significance level for the null hypothesis tests was set at .05. We calculated *t*-tests for positive and negative affect score changes, perceived risks and benefits changes, and the effect size of Cohen's d using the following equation: $d=(M-\mu)/SD$, in which M is the sample mean, μ is the theoretical mean under the null hypothesis (i.e., 0), and SD is the standard deviation of the sample. Cohen's d was interpreted as 0.2

(small), 0.5 (moderate), and 0.8 (large). Partial eta squared ($\eta_p{}^2$) for effect size of factors in the one-way ANOVA was interpreted as .01 (small), .06 (moderate), and .14 (large).

Moreover, path analysis was conducted to comprehensively examine the relationships among variables using the *lavaan* R package (Version 0.6-8). The path model shown in Fig. 1 was constructed based on the following hypotheses: (1) positive affect at Time 2 will increase perceived benefits and decrease perceived risks, (2) negative affect at Time 2 will increase perceived risks and decrease perceived benefits, (3) the betting recklessness will decrease as the perceived risks increase, whereas it will increase as the perceived benefits increase. We estimated the path model's parameters using the robust estimation method (MLR; Yuan & Bentler, 2000) because we judged that the variables did not satisfy multivariate normality.

Ethics Statement

This experiment was conducted after obtaining the approval of Kyoto University's Graduate School of Education's ethics committee. Written informed consent was obtained from all the participants before and after the experiment. Careful debriefing was conducted after the experiment about inevitable deceptions, including the purpose and experimental manipulations and the need for deception to eliminate the participants' suspicions. None of the participants withdrew their consent for data use after the debriefing.

Results

First, we report the results of between-group differences in positive and negative affect scores and perceived risk-benefit at the two time-points, Times 1 and 2, and degree of change between the time-points, Times 1 to 2 and Times 2 to 3. Next, reckless betting during the second session and its time-series changes are reported. Finally, we reported the results of the path analysis and relationships among the variables.

Manipulation Check

The mean value of the estimated percentage of winning trials during the first session for each group was calculated, which indicated the following: the winning group; 70.1 (*SD* =11.2), the moderate winning group; 28.4 (*SD* =15.8), and the losing group; 13.76 (*SD* =7.5). The mean values were compared using a one-way ANOVA to check if the experimental manipulation of the number of wins and losses in the first session was successful, which indicated that the main effect of the group was significant at the 5% level (F (2, 52) = 116.22, p < .001, $\eta_p{}^2$ = .817, 95% CI of $\eta_p{}^2$ [.712, .864]). Multiple comparisons using the Shaffer method indicated that all the between-group differences were significant at the 5% level (ps and adjusted ps <.001). These results supported that the manipulation during the first session was successful.

Positive and Negative Affect

The mean PA and NA scores of each group at three time points: before the first session (Time 1), between the sessions (Time 2), and after the second session (Time 3) were calculated (Table 1). First, the mean values of PA and NA scores at Time 1 were compared using a one-way ANOVA, which indicated that the main effect of the group was not significant at the 5% level (F (2, 52) = 0.06, p = .94, $\eta_p{}^2$ = .002, 95% CI of $\eta_p{}^2$ [.000, .029]; F (2, 52) = 0.29, p = .75, $\eta_p{}^2$ = .011, 95% CI of $\eta_p{}^2$ [.000, .089], respectively).

Next, the mean values of PA and NA at Time 2 were compared using a one-way ANOVA, which indicated that the main effect of the group on NA scores was statistically significant at the 5% level (F (2, 52) = 4.08, p = .02, $\eta_p{}^2$ = .136, 95% CI of $\eta_p{}^2$ [.001, .290]). Multiple comparisons indicated that between-group differences were statistically significant at .05 level only between winning and losing groups and winning and moderate winning groups (ps and adjusted ps < .05). Conversely, the main effect of the group on PA scores was not significant at the 5% level (F (2, 52) = 0.84, p = .44, $\eta_p{}^2$ = .031, 95% CI of $\eta_p{}^2$ [.000, .141]). Fig. 3 shows the mean values of each group at Time

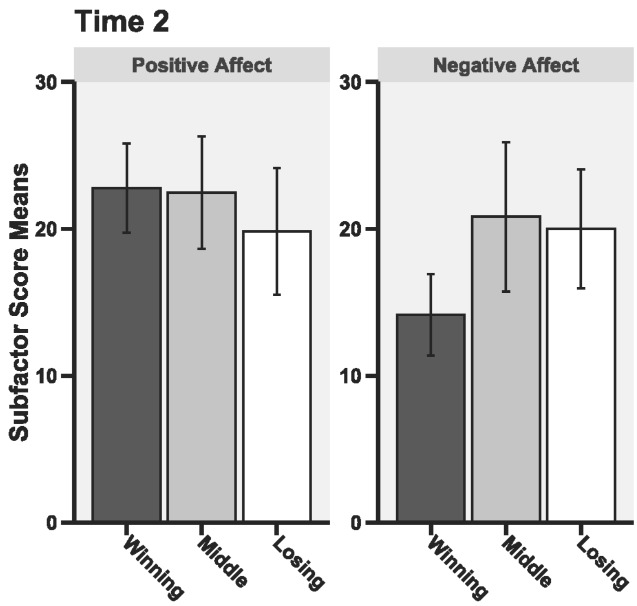
Table 1

Means and *SD*s of the positive (PA) and negative affect (NA) scores. The affect scores range from 10 to 50. The values in parentheses indicate *SD*s.

Group	**PA**			**NA**		
	Time 1	Time 2	Time 3	Time 1	Time 2	Time 3
Winning	21.8 (5.41)	22.8 (6.66)	22.2 (5.61)	13.8 (3.70)	14.1 (6.05)	17.1 (5.20)
Middle	22.6 (7.56)	22.5 (7.48)	24.2 (8.79)	14.5 (5.29)	20.8 (9.89)	18.9 (8.91)
Losing	22.1 (8.52)	19.8 (8.39)	22.4 (8.80)	13.4 (4.00)	20.0 (7.87)	16.9 (4.95)

Fig.3

Means and 95% confidence intervals of positive (PA) and negative affect (NA) scores after the 1st session (Time 2). A higher bar indicates a higher subfactor score (min. 10, max. 50).



2 and the 95% confidence interval, indicating that the NA score of the winning group was lower than those of the other two groups and that the PA score of the losing group was lower than those of the other two groups.

Changes in Positive and Negative Affect

The degree of change in PA and NA scores of each group was calculated to examine changes in positive and negative affect from Time 1 to 2 and from Time 2 to 3. Moreover, a one-sample *t*-test was conducted to examine whether the degree of change might differ from 0. Table 2 shows the mean degree of change and the results of the one-sample *t*-test. The change in PA from Time 1 to 2 was significant in the losing group at

Table 2

Mean changes in positive (PA) and negative affect (NA) scores and one-sample *t*-test results. The values in parentheses following the effect size indicate the 95% CIs computed by the bootstrap method (n = 1000).

Group	Positive Affect									
	Time 2 – Time 1					Time 3 – Time 2				
	M (*SD*)	*t*	*df*	*p*	Cohen's *d*	*M* (*SD*)	*t*	*df*	*p*	Cohen's *d*
Winning	1.0 (3.06)	1.43	20	.17	0.31 [-0.14, 0.77]	-0.6 (6.27)	-0.42	20	.68	-0.09 [-0.53, 0.40]
Middle	-0.1 (5.18)	-0.09	16	.93	-0.02 [-0.56, 0.47]	1.8 (4.58)	1.59	16	.13	0.38 [-0.06, 0.89]
Losing	-2.2 (3.83)	-2.40	16	.03	-0.58 [-1.11, -0.21]	2.6 (9.15)	1.17	16	.26	0.28 [-0.18, 0.90]

Group	Negative Affect									
	Time 2 – Time 1					Time 3 – Time 2				
	M (*SD*)	*t*	*df*	*p*	Cohen's *d*	*M* (*SD*)	*t*	*df*	*p*	Cohen's *d*
Winning	0.3 (3.95)	0.39	20	.70	0.08 [-0.41, 0.46]	3.0 (5.20)	2.25	20	.04	0.49 [0.06, 1.19]
Middle	6.3 (7.24)	3.59	16	.002	0.87 [0.54, 1.46]	-1.9 (5.09)	-1.53	16	.15	-0.37 [-0.78, 0.16]
Losing	6.6 (4.00)	3.72	16	.002	0.90 [0.54, 1.51]	-3.1 (7.42)	-1.73	16	.10	-0.42 [-0.8, -0.03]

the 5% level, whereas it was not significant in the winning or the moderate winning groups. NA's change from Time 1 to 2 was significant in the moderate winning and losing groups at the 5% level, whereas it was not significant in the winning group.

Next, a one-sample *t*-test was conducted for each group to examine whether the degree of change from Time 2 to 3 differed from 0. The results indicated that PA scores' change was not statistically significant at the 5% level in any group. However, the NA scores were statistically significant at the 5% level only in the winning group, whereas it was not significant in the moderate winning or the losing groups.

Fig. 4 shows the mean degree of change in PA and NA scores and the 95% confidence interval. The left panel indicates a decrease in positive affect and an increase in negative affect in the losing group, and an increase in negative affect in the moderate winning group before and after the first session. The right panel indicates an increase in

Fig.4

Mean changes in the positive (PA) and negative affect (NA) scores. A bar above zero indicates an increase in the subscale score, while a bar below zero indicates a decrease.

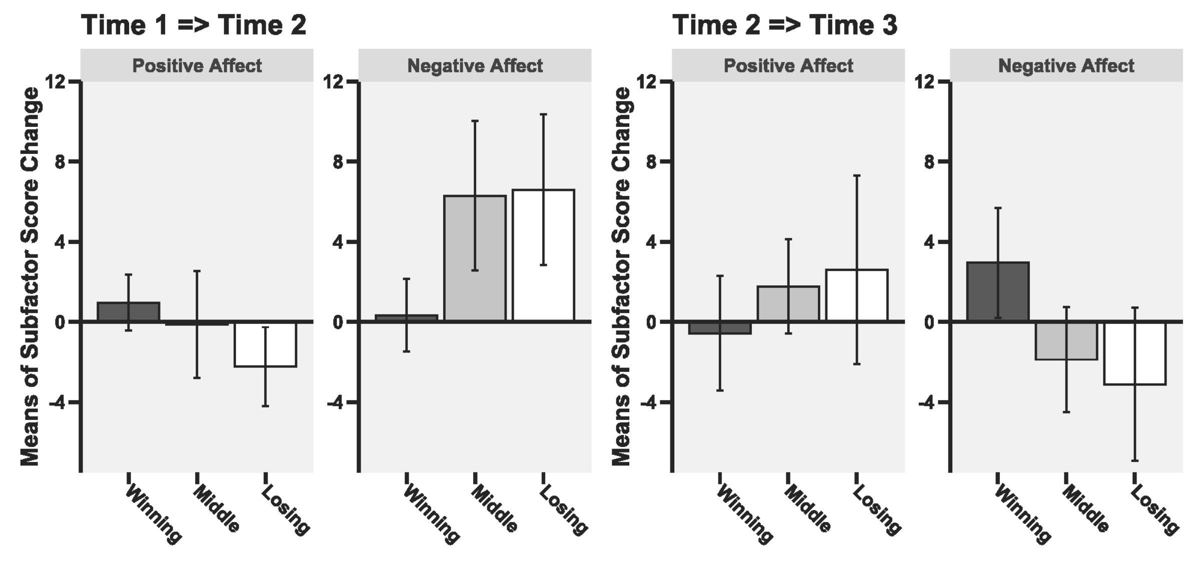


Table 3

Means and *SD*s of the perceived risk and benefit. The ratings range from 1 to 7. The values in parentheses indicate *SD*s.

Group	Perceived Risk		Perceived Benefit	
	Time 1	Time 2	Time 1	Time 2
Winning	3.9 (1.61)	4.7 (1.59)	5.3 (0.85)	5.3 (1.15)
Middle	4.6 (2.06)	5.0 (2.03)	4.8 (1.81)	4.4 (1.37)
Losing	4.0 (1.84)	5.4 (1.33)	5.3 (1.16)	4.2 (1.64)

negative affect before and after the second session only in the winning group.

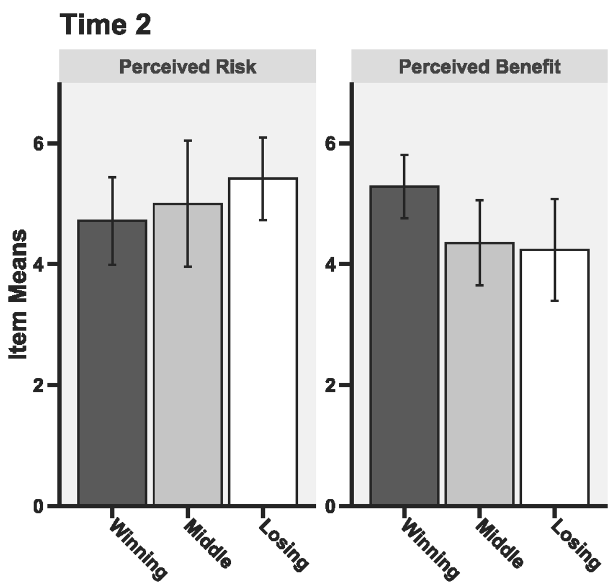
Perceived Risk-Benefit

Table 3 shows the mean values of perceived risk-benefit before the first session (Time 1), between the sessions (Time 2), and after the second session (Time 3) for each group. First, the perceived risks and perceived benefits at Time 1 were compared through a one-way ANOVA. The results indicated that the main effect of the group was not statistically significant at the 5% level either for perceived risks or benefits (F (2, 52) = 0.73, p = .49, $\eta_p{}^2$ = .028, 95% CI of $\eta_p{}^2$ [.000, .133]; F (2, 52) = 0.75, p = .48, $\eta_p{}^2$ = .028, 95% CI of $\eta_p{}^2$ [.000, .135], respectively).

Next, the mean values of perceived risk and perceived benefit at Time 2 were compared through a one-way ANOVA. The results indicated that the main effect of the group on perceived benefit was statistically significant at the 5% level (F (2, 52) = 3.38, p = .04, $\eta_p{}^2$ = .115, 95% CI of $\eta_p{}^2$ [.000, .266]). The results of multiple comparisons using the Shaffer method indicated that the between-group differences were not statistically significant at the 5% level (between winning and losing groups: p = .02, adjusted p = .07; between winning and moderate winning groups: p = .04, adjusted p = .07; between moderate winning and losing groups: p = .80, adjusted p = .80). Conversely, the main effect of the group on perceived risk was not statistically significant at the 5% level (F (2, 52) = 0.82, p = .44, $\eta_p{}^2$ = .031, 95% CI of $\eta_p{}^2$ [.000, .141]). Fig. 5 shows

Fig.5

Means and 95% confidence intervals of perceived risk-benefit after the 1st session (Time 2). A higher bar indicates a higher item score (min. 1, max. 7).



the mean values of each group at Time 2 and the 95% confidence interval.

Changes in Perceived Risk-Benefit

Changes in perceived risk-benefit from Time 1 to Time 2 were examined by calculating the degree of change in each group (i.e., Time 2 – Time 1). Moreover, a one-sample *t*-test was conducted for each group to examine if the degree of change was different from 0. Table 4 shows the mean degree of changes and the results of the one-

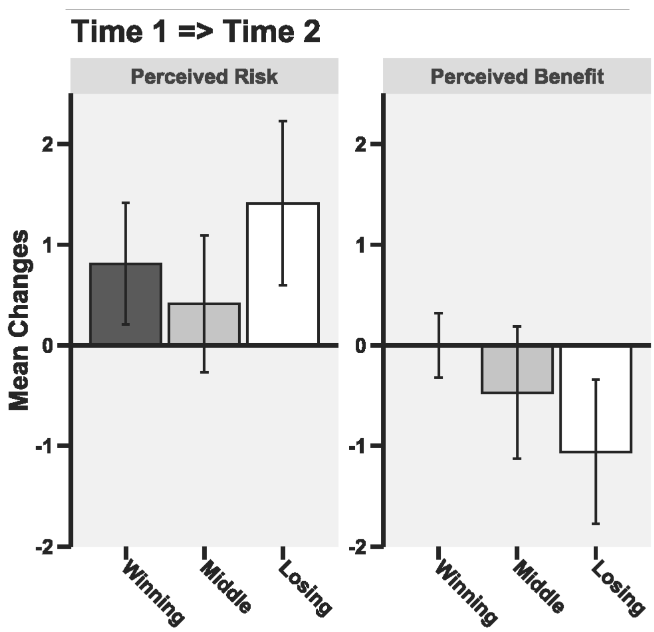
Table 4

Mean changes in perceived risk-benefit, and one-sample *t*-test results. The values in parentheses following the effect size indicate the 95% CIs computed by the bootstrap method (*n* = 1000).

Group	Perceived Risk Time 2 – Time 1					Perceived Benefit Time 2 – Time 1				
	M (*SD*)	*t*	*df*	*p*	Cohen's *d*	*M* (*SD*)	*t*	*df*	*p*	Cohen's *d*
Winning	0.8 (1.33)	2.79	20	.01	0.61 [0.27, 1.00]	0.0 (0.71)	0	20	1	0 [-0.51, 0.40]
Middle	0.4 (1.33)	1.28	16	.22	0.31 [-0.24, 0.63]	-0.5 (1.28)	-1.51	16	.15	-0.37 [-1.05, 0.13]
Losing	1.4 (1.58)	3.68	16	.002	0.89 [0.59, 1.39]	-1.1 (1.39)	-3.14	16	.006	-0.76 [-1.18, -0.49]

Fig.6

Mean changes in perceived risk and benefit. A bar above zero indicates an increase in the item score, while a bar below zero indicates a decrease.



sample *t*-test.

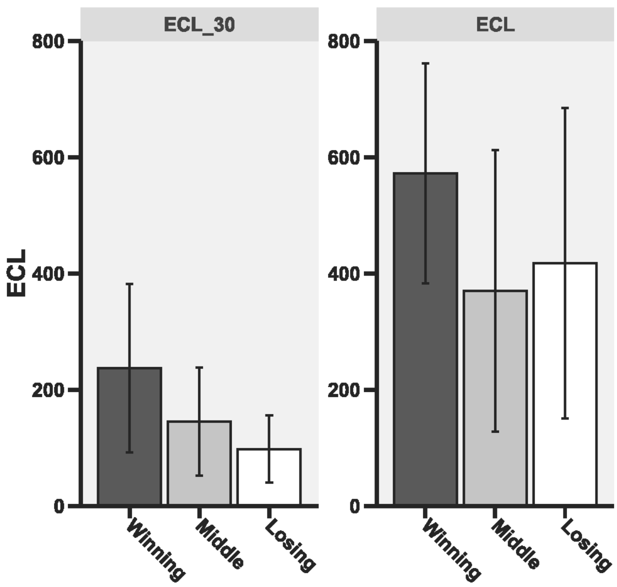
Changes in perceived risk were statistically significant at the 5% level in winning and losing groups, whereas it was not significant in the moderate winning group. The degree of perceived benefit was statistically significant at the 5% level only in the losing group, whereas it was not significant in the winning or moderate winning groups. Fig. 6 shows the mean degree of change in perceived risk-benefit from Times 1 to 2 and the 95% confidence interval. The figure indicates an increase in perceived risk and a decrease in perceived benefit before and after the first session in the losing group and increased perceived risk in the winning group.

Recklessness

The mean value of ECL in each group measured during the second session was calculated: 572.6 (416.0), the moderate winning group; 370.2 (471.0), and the losing

Fig.7

Means and 95% confidence intervals of recklessness during the first 30 trials of the second session (ECL_30) and the 2nd session (ECL). A higher bar indicates a higher value.



group; 417.8 (519.0). The mean values were compared using a one-way ANOVA. The result indicated that the main effect of the group was not statistically significant at the 5% level (F (2, 52) = 1.00, p = .38, $\eta_p{}^2$ = .037, 95% CI of $\eta_p{}^2$ [.000, .152]). Next, the mean value of ECL_30 in each group was calculated: the winning group; 237.1 (318.8), the moderate winning group; 145.2 (180.9), and the losing group; 97.8 (112.1). The mean values were compared using a one-way ANOVA. The result indicated that the main effect of the group was not statistically significant at the 5% level, and the effect size of the sample was smaller than in previous studies (F (2, 52) = 1.82, p = .17, $\eta_p{}^2$ = .065, 95% CI of $\eta_p{}^2$ [.000, .200]). The above results indicated no between-group differences in reckless betting for either the whole second session or the first 30 trials of the second session.

Fig. 7 shows the mean ECL values for the first 30 trials and the whole of the second session, as well as the 95% confidence interval. Reckless betting in the first 30 trials was higher in the winning group than the losing group, and the reckless betting of the moderate winning group was located between the winning and losing groups. On the other hand, reckless betting in the whole session was the highest in the winning group, followed by the losing and moderate winning groups such that the order of losing and moderate winning groups was changed.

Time-series Changes in Recklessness

Time-series analysis was conducted to examine time-series changes in recklessness regarding iECL (i.e., recklessness measured at each trial) as time-series data. Fig. 8 shows each group’s estimated time-series changes of betting recklessness. The losing group showed multiple peaks in betting recklessness, especially around the 90th and the 100th trials. Conversely, the moderate winning and winning groups showed a

Fig. 8

Time series changes and 95% credible intervals of recklessness during the 2nd session. The solid line indicates the Expected A Posteriori (EAP) estimates of μ_t, and the area between upper and lower dotted lines indicates the 95% credible interval.

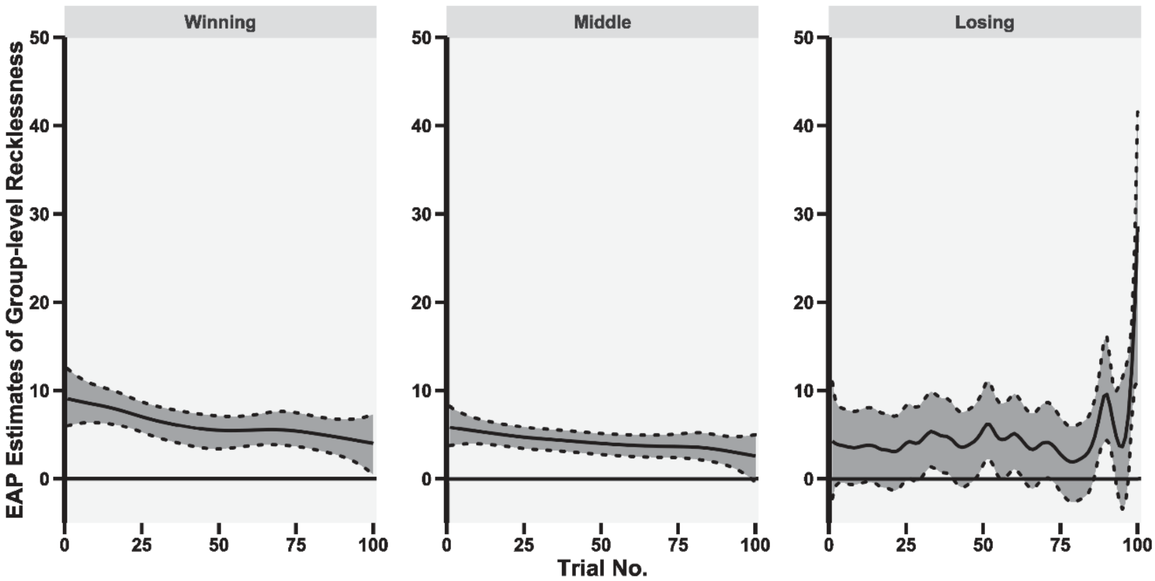
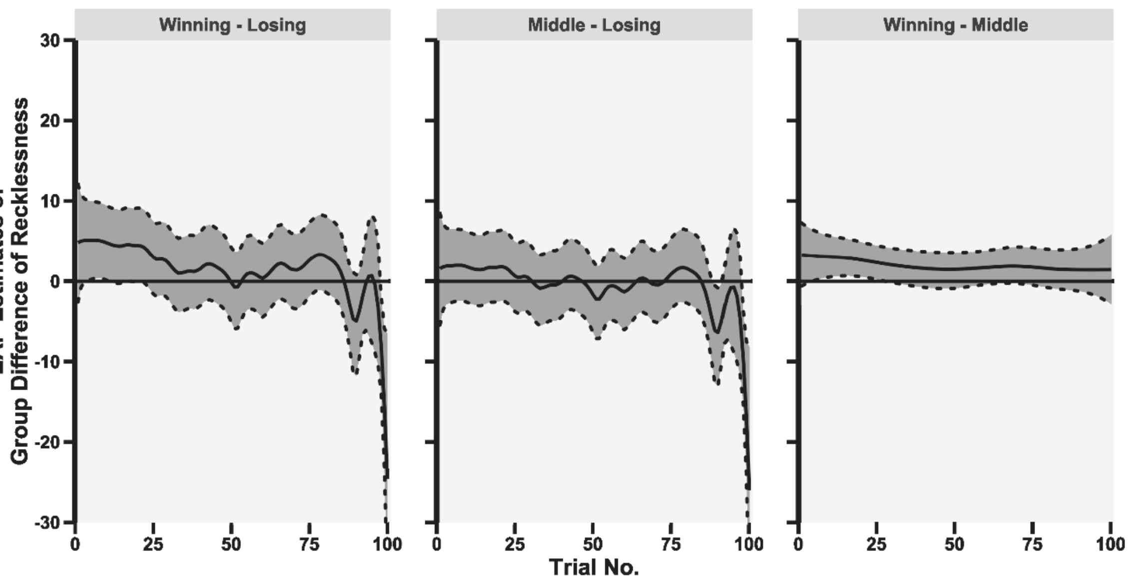


Fig. 9

Time series changes and 95% credible intervals of group difference in recklessness during the 2nd Session. The solid line indicates the EAP estimates of group difference of μ_t, and the area between upper and lower dotted lines indicates the 95% credible interval.



gradual decline in recklessness throughout the 2nd session. It can be seen from the figure that the recklessness level in the winning group was higher than the other two groups until approximately the 20th trial, after which the difference becomes small.

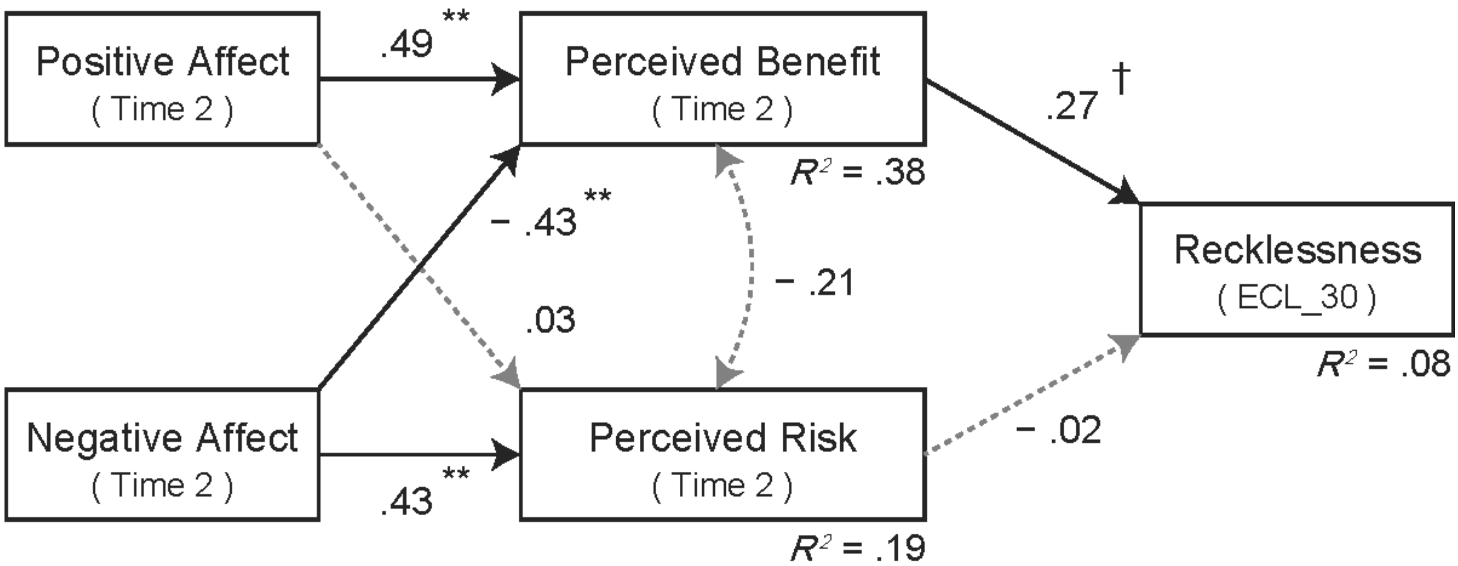
Posterior distribution of group differences was calculated using each group's posterior distribution of μ_t. Fig. 9 shows time-series changes in between-group differences of recklessness. We identified periods in which the 95% credible interval of the EAP estimate did not contain zero to identify periods in which the group difference was statistically significant. The results indicated a statistically significant difference in recklessness from the 4th to 10th trials, 17th, 20th, 21st, and from the 98th to 100th trials between winning and losing groups. Moreover, a statistically significant difference was indicated between moderate winning and losing groups, from the 89th to 91st trials as well as from the 98th to 100th trials. Furthermore, a statistically significant difference was indicated between the winning and moderate winning groups, from the 5th to 27th trials.

Path Analysis

We concluded that it was not reasonable to assume that positive and negative affect and perceived risk-benefits had an impact on recklessness in the entire second session by considering the results of the time-series analysis. Therefore, we used ECL_30 as the variable of recklessness instead of ECL. Fig. 10 shows the path model based on our hypothesized model (Fig. 1) and the estimated standardized path coefficients (for correlations among variables, unstandardized path coefficients, and test statistics, see Supplementary 1 and 2 in Online Resource). The model indicated a higher than moderate level of goodness-of-fit for specific indices: $\chi^2(2)$ = 2.94 [p =.23], RMSEA = .094 [.000, .305], CFI = .975, TLI = .886, SRMR = .052. A consistent relationship with our

Fig. 10

Path model, standardized estimates of path coefficients and R squared values. The symbols attached to the path coefficients denote the results of significance tests: **: p <.01, †: p <.10.



hypothesis was observed in the path from positive and negative affect to perceived benefits and the path from negative affect to perceived risks. Conversely, the path from positive affect to perceived risks indicated hardly any influence, which did not support the study hypothesis. Moreover, it can be seen from the figure that perceived benefits increased recklessness, whereas perceived risks did not influence recklessness.

Discussion

Previous studies have consistently reported that prior experiences of many wins lead to more reckless betting than experiencing many prior losses (Cummins et al., 2009; Taoka & Ariga, 2019). The present study's first aim was to examine the effects of risk-benefit perception and positive-negative affect during gambling on reckless betting, and the second aim was to examine time-series changes in reckless betting. We conducted an experiment using a gambling task in which the number of wins and losses were manipulated in the first session under three conditions: winning, moderate winning, and losing. Reckless betting during the second session was assessed by calculating ECL based on bet size and winning probability of each trial. Moreover, positive and negative affect and risk-benefit perception of betting were assessed at multiple time-points to examine changes caused by the experimental manipulation.

The results indicated that prior experiences of wins and losses altered affective states and risk-benefit perception of betting during the gambling. The mean positive affect score in the losing group was lower than in the winning and moderate winning groups, but the differences between groups were not statistically significant. On the other hand, the present study indicated that the winning group's negative affect scores were significantly lower than those in the other two groups. These patterns of prior winning and losing experiences and affect are inconsistent with the results of Cummins et al. (2009). Further analysis of affect scores revealed that positive affect decreased and negative affect increased in participants who experienced many losses, whereas participants who experienced many wins did not show these changes (see Fig. 4). These results suggest that many wins or few losses do not necessarily lead to arousing positive affect but rather result in maintaining the current affective states during gambling. In contrast, many losses or few wins lead to the elicitation of negative affect and depletion of positive affect. An increase in perceived risk and a decrease in perceived benefits were observed in the losing group that corresponded to these changes in affective states induced by many losses (see Fig. 6). These results support the findings of previous studies on risk perceptions in which the arousal of negative affect resulted in an increase in perceived risk (Sobkow et al., 2016). Our results are also consistent with the perspective of affect heuristic (Slovic et al., 2007), which predicts higher risk perception and lower benefit perception with negative affect. These relationships among negative affect and risk-benefit perceptions were partly supported by the path analysis results (Fig. 10). Considering there was no change in perceived benefits observed in the winning group, these results suggested that changes in affective states and risk-benefit perception caused by experiencing losses play a crucial role in inhibiting the losing group's reckless betting.

However, the perceived risk also increased in the winning group (see Fig. 6), which might explain why our results on recklessness (see the left panel of Fig. 7) were inconsistent with previous studies (Cummins et al., 2009; Taoka & Ariga, 2019). There was little change in the affective states of the winning group's participants. It implies that factors other than affect might have influenced their risk perception or moderated the relationship between winning experiences and risk perception. One explanation might be that many winning experiences were perceived as precursors of future adverse outcomes, rather than the mere accumulation of positive outcomes. The negative perception toward a series of positive outcomes can be explained by the idea of the *luck resource belief*, which is the belief that luck is a kind of consumable resource (Murakami, 2009). Individuals with the luck resource belief feel that their luck has been consumed by a series of positive outcomes and tend to have negative expectations or underestimate the probability of future success as a result (Murakami, 2009). Moreover, high numeracy, which is the ability to understand numbers and probability (Peters et al., 2006), could also result in the negative evaluation of a series of positive outcomes because those with high numeracy would easily detect the difference between the mathematically expected frequency of wins and the actual one, and predict that a losing streak would follow a winning streak. In this respect, we should note the group differences in numeracy between Japan and the United States, where the experiment of Cummins et al. (2009) was conducted. Japan’s numeracy test score in the Program for the International Assessment of Adult Competencies (PIAAC) administered by OECD (2019) ranked at the top among OECD member countries, whereas that of the US was significantly below the OECD mean, which could explain the differences between this study and the study by Cummins et al. (2009). The effect of prior winning experiences in this study might have been weakened by the luck-based negative expectation of future outcomes or by individual differences in numeracy. However, we did not address such individual differences in this study. It is suggested that future research should consider the moderation of prior winning experiences by individual beliefs, thinking styles, numerical abilities, among others.

The results discussed so far indicated that prior experiences of wins and losses could alter the participants’ affective states and risk-benefit perceptions during a gambling task, especially when they have experienced many losses. How did these psychological variables relate to reckless betting? The path analysis (Fig. 10) answers this question by showing that positive and negative affect influenced recklessness through the benefit perception of betting. Moreover, the signs of the path coefficients among these variables were as we hypothesized (Fig. 1). Therefore, our hypotheses regarding the relationships among affect, benefit perception, and recklessness were supported, except that no relationships were observed among positive affect, perceived risk, and recklessness. As discussed above, risk perception may have been moderated by specific individual traits or higher-order cognitions, which would require further research to clarify. These findings are important because no study to date has explored the relationships among affect, risk-benefit perception, and reckless betting.

We now turn to this study's second aim, which is the within-session time-series changes in betting recklessness. The time-series analysis results indicated that the recklessness of the winning group, which was at the highest level at the beginning of the second session, gradually declined (Fig. 8). Moreover, the negative affect in the winning group's participants increased after the second session compared to before the second session (Fig. 4). These results allow us to infer that the evocation of negative affect inhibited reckless betting and demonstrated that reckless betting caused by prior winning experiences is not necessarily maintained throughout the session and could diminish in response to subsequent gambling outcomes and affective changes. Similar within-session changes in betting behaviors were also observed in a recent study examining baccarat players at casinos by Abe et al. (2020), who reported that baccarat players that experienced sequential losses had a reduced tendency to bet on *longshots* (i.e., hands with low winning probability and high dividend rates). Therefore, the results of the current laboratory study were similar to the observation of real gamblers' betting behaviors in a simpler gambling task reported by Abe et al.

Another significant result of the time-series analysis was that participants in the losing group made reckless bets in the final stage of the task (Fig. 8), suggesting that they tried to offset their accumulated losses and turn the game around, which is typical of loss-chasing. Thaler and Johnson (1990) suggested that gamblers make risk-seeking bets even when faced with losses because they perceive that outcomes offering a chance to break even are attractive (break-even effect). Therefore, betting benefits are temporally perceived as high, which leads to reckless betting in the final stage of the task. However, whether their behavior is loss-chasing remains hypothetical due to the lack of evidence regarding the losing group's participants' motives and intentions that made reckless bets at the end of the task. Nevertheless, this is a novel finding suggesting that reckless betting can occur in the final stage of a gambling session even after experiencing many losses.

The possibility of reckless betting at the end of a gambling task might be influenced by the reward determination method as well as prior experiences of wins and losses. We determined the number of rewards and paid the participants immediately after task completion, which would make it easy for participants to imagine the break-even result. The proximity of task completion and reward payout might result in a break-even effect in this experiment. The method we used seemingly reflected real gambling situations well; nevertheless, taking account of situational factors might help us better understand this new type of reckless betting and also address inconsistent findings of previous studies that have examined the effects of previous wins and losses on risky betting behaviors (Cummins et al., 2009; Leopard, 1978; Smith et al., 2009; Suhonen & Saastamoinen, 2018; Thaler & Johnson, 1990).

Finally, we wish to mention the specific limitations of this study and several research questions for future studies. This study's first limitation is that reckless betting was not fully explained by positive and negative affect and risk-benefit perception. The model proposed in this study explained only 8% of the variance of reckless betting (i.e., ECL_30; see the R-squared value in Fig. 10), suggesting the need to explore psychological factors other than affect and risk-benefit perception, including trait factors influencing reckless betting. If prior experiences and affect play a key role in reckless betting, then individual differences in susceptibility to affective and experiential influences must be considered. For example, it has been indicated that individuals with high numeracy are less likely to be affected by non-numerical information such as mood in making judgments and decision-making (for review, Peters, 2012). Modulation by higher-order cognitive processes deriving by individual traits such as beliefs, thinking styles, and numerical skills should also be considered.

The second limitation is that it is not clear which cognitive processes in the Acey-Deucey Task were influenced by prior experiences and affective states. The Acey-Deucey Task might involve a two-stage cognitive process: estimating the winning probability based on dealt cards and determining bet size based on the winning probability. It is essential to identify which of these cognitive processes are influenced by prior experiences and affective states to elucidate the underlying mechanisms of reckless betting. Expressing these cognitive processes as a mathematical model, or *cognitive modeling* might provide a more stringent test for this kind of hypothesis. A cognitive model seems very useful because it allows us to detect individual differences in each cognitive process as differences in parameter estimates. Several studies have developed cognitive models for well-known gambling tasks, including the Iowa Gambling Task, the Cambridge Gambling Task, and the Balloon Analogue Risk Task, among others (Busemeyer & Stout, 2002; van Ravenzwaaij et al., 2011; Romeu et al., 2019), which have helped us understand individual differences in decision-making processes during these tasks.

In summary, the results of this study add to the reckless betting literature in two ways. Firstly, we provided affect and risk-benefit perception-based empirical evidence of the underlying mechanisms of reckless betting. Regarding why prior winning experiences lead to reckless betting, this study can partially answer that it is because not having losing experiences maintain affective states and perceived benefits of betting. Second, time-series analysis revealed the within-session time-series changes in recklessness. One of the noteworthy findings from the time-series analysis was that participants experiencing many losses in the first session made reckless bets intensively at the end of the next session of the gambling task, suggesting a potential link between reckless betting and loss-chasing. We have mentioned the need to address the influence of individual traits and higher-order cognitions as issues remaining for future studies. The accumulation of psychological findings related to the underlying mechanisms of reckless betting is expected to lead to more effective prevention measures for problem gambling and gambling addiction.

References

Abe, N., Nakai, R., Yanagisawa, K., Murai, T., & Yoshikawa, S. (2020). Effects of sequential winning vs. losing on subsequent gambling behavior: analysis of empirical data from casino baccarat players. *International Gambling Studies*, doi: 10.1080/14459795.2020.1817969

Brose, A., Schmiedek, F., Gerstorf, D., & Voelkle, M. C. (2020). The measurement of within-person affect variation. *Emotion*, *20*(4), 677-699. doi: 10.1037/emo0000583

Busemeyer, J. R., & Stout, J. C. (2002). A contribution of cognitive decision models to clinical assessment: decomposing performance on the Bechara gambling task. *Psychological Assessment*, *14*(3), 253-262. doi: 10.1037/1040-3590.14.3.253

Calado, F., Alexandre, J., & Griffiths, M. D. (2017). Prevalence of adolescent problem gambling: A systematic review of recent research. *Journal of Gambling Studies*, *33* (2), 397-424. doi: 10.1007/s10899-016-9627-5

Cummins, L. F., Nadorff, M. R., & Kelly, A. E. (2009). Winning and positive affect can lead to reckless gambling. *Psychology of Addictive Behaviors, 23* (2), 287-294. doi: 10.1037/a0014783

Delfabbro, P. (2004). The stubborn logic of regular gamblers: Obstacles and dilemmas in cognitive gambling research. *Journal of Gambling Studies*, *20* (1), 1-21. doi: 10.1023/B:JOGS.0000016701.17146.d0

Fortune, E. E., & Goodie, A. S. (2012). Cognitive distortions as a component and treatment focus of pathological gambling: a review. *Psychology of Addictive Behaviors*, *26* (2), 298-310. doi: 10.1037/a0026422

Gelman, A., & Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical Science*, *7*(4), 457-472.

Haase, C. M., & Silbereisen, R. K. (2011). Effects of positive affect on risk perceptions in adolescence and young adulthood. *Journal of Adolescence, 34* (1), 29-37. doi: 10.1016/j.adolescence.2010.03.004

Hayano, S., Dong, R., Miyata, Y., & Kasuga, S. (2021). The study of differences by region and type of gambling on the degree of gambling addiction in Japan. *Scientific Reports*, *11* (1), 1-9. doi: 10.1038/s41598-021-92137-8

Johnson, E. J., & Tversky, A. (1983). Affect, generalization, and the perception of risk. *Journal of Personality and Social Psychology, 45*(1), 20-31. doi: 10.1037/0022-3514.45.1.20

Kawahito, J., Otsuka, Y., Kaida, K., & Nakata, A. (2011). Reliability and validity of the Japanese version of 20-item positive and negative affect schedule. *Hiroshima Psychological Research*, *11*, 225-240. doi: 10.15027/32396 (In Japanese with English abstract)

Ladouceur, R., & Walker, M. (1996). A Cognitive Perspective on Gambling. In Salkovskis, P. M. (Ed), *Trends in cognitive and behavioural therapies* (pp. 89-120). New York: Wiley.

Leopard, A. (1978). Risk preference in consecutive gambling. *Journal of Experimental Psychology: Human Perception and Performance*, *4* (3), 512-528. doi: 10.1037/0096-1523.4.3.521

Lerner, J. S., & Keltner, D. (2000). Beyond valence: Toward a model of emotion-specific influences on judgement and choice. *Cognition & Emotion*, *14* (4), 473-493. doi: 10.1080/026999300402763

Murakami, K. (2009). Do “Lucky” outcomes occur repeatedly?: Application of the “Luck Resource Belief” perspective to attitudes toward uncertain events. *Japanese Journal* *of Social Psychology*, *25* (1), 30-41. doi: 10.14966/jssp.KJ00005698865 (In Japanese with English abstract)

Nygren, T. E., Isen, A. M., Taylor, P. J., & Dulin, J. (1996). The influence of positive affect on the decision rule in risk situations: Focus on outcome (and especially avoidance of loss) rather than probability. *Organizational Behavior and Human Decision Processes, 66* (1), 59-72. doi: 10.1006/obhd.1996.0038

O'Connor, J., & Dickerson, M. (2003). Definition and measurement of chasing in off-course betting and gaming machine play, *Journal of Gambling Studies, 19* (4), 359-386. doi: 10.1023/A:1026375809186

Patalano, A. L., Saltiel, J. R., Machlin, L., & Barth, H. (2015). The role of numeracy and approximate number system acuity in predicting value and probability distortion. *Psychonomic Bulletin & Review*, *22* (6), 1820-1829. doi: 10.3758/s13423-015-0849-9

Peirce, J., Gray, J. R., Simpson, S., MacAskill, M., Höchenberger, R., Sogo, H., Kastman, E., & Lindeløv, J. K. (2019). PsychoPy2: Experiments in behavior made easy. *Behavior Research Methods, 51*(1), 195-203. doi: 10.3758/s13428-018-01193-y

Peters, E., Västfjäll, D., Slovic, P., Mertz, C. K., Mazzocco, K., & Dickert, S. (2006). Numeracy and decision making. *Psychological Science, 17* (5), 407-413. doi: 10.1111/j.1467-9280.2006.01720.x

Peters, E. (2012). Beyond comprehension: The role of numeracy in judgments and decisions. *Current Directions in Psychological Science, 21* (1), 31-35. doi: 10.1177/0963721411429960

Romeu, R. J., Haines, N., Ahn, W.Y., Busemeyer, J. R., & Vassileva, J. (2020). A computational model of the Cambridge gambling task with applications to substance use disorders. *Drug and Alcohol Dependence*, *206*, 107711. doi: 10.1016/j.drugalcdep.2019.107711

Slovic, P., Finucane, M. L., Peters, E., & MacGregor, D. G. (2007). The affect heuristic. *European Journal of Operational Research, 177* (3), 1333-1352. doi: 10.1016/j.ejor.2005.04.006

Smith, G., Levere, M., & Kurtzman, R. (2009). Poker player behavior after big wins and big losses. *Management Science*, *55* (9), 1547-1555. doi: 10.1287/mnsc.1090.1044

Sobkow, A., Traczyk, J., & Zaleskiewicz, T. (2016). The affective bases of risk perception: negative feelings and stress mediate the relationship between mental imagery and risk perception. *Frontiers in Psychology, 7*. doi: 10.3389/fpsyg.2016.00932

Suhonen, N., & Saastamoinen, J. (2018). How do prior gains and losses affect subsequent risk taking? New evidence from individual-level horse race bets. *Management Science*, *64* (6), 2797-2808. doi: 10.1287/mnsc.2016.2679

Takada, T., & Yukawa, S. (2012). Effects of winning versus losing on reckless gambling behavior and the relationships with affects. *Japanese Journal of Research on Emotion*, *19* (3), 98-105. doi: 10.4092/jsre.19.98 (In Japanese with English abstract)

Taoka, D., & Ariga, A. (2019, January). Winners do not stop gambling, but become reckless gamblers. *Paper presented at 2019 11th International Conference on Knowledge and Smart Technology (KST)* (pp. 199-202). IEEE. doi: 10.1109/KST.2019.8687675

Thaler, R. H., & Johnson, E. J. (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management Science, 36* (6), 643-660. doi: 10.1287/mnsc.36.6.643

van Ravenzwaaij, D., Dutilh, G., & Wagenmakers, E. J. (2011). Cognitive model decomposition of the BART: Assessment and application. *Journal of Mathematical Psychology*, *55* (1), 94-105. doi: 10.1016/j.jmp.2010.08.010

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales. *Journal of Personality and Social Psychology, 54* (6), 1063-1070. doi: 10.1037//0022-3514.54.6.1063

Wright, W. F., & Bower, G. H. (1992). Mood effects on subjective probability assessment. *Organizational Behavior and Human Decision Processes, 52* (2), 276-291. doi: 10.1016/0749-5978(92)90039-A

Yuan, K. H., & Bentler, P. M. (2000) Three likelihood-based methods for mean and covariance structure analysis with non-normal missing data. In M. E. Sobel, & M. P. Becker (Eds.), *Sociological methodology 2000* (pp. 165-200). Washington, DC: The American Sociological Association. doi: 10.1111/0081-1750.00078

Zhang, K., & Clark, L. (2019). Loss-chasing in gambling behavior: neurocognitive and behavioural economic perspectives. *Current Opinion in Behavioural Sciences, 31*, 1-7. doi: 10.1016/j.cobeha.2019.10.006