Optimal motor decision-making through competition with opponents

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Abstract

Even though optimal decision-making is essential for sports performance and fine motor control, it has been repeatedly confirmed that humans show a strong risk-seeking bias, selecting a risky strategy over an optimal solution[1-9]. Despite such evidence, how to promote optimal decision-making remains unclear. Here, we propose that interactions with other people can influence motor decision-making and improve risk-seeking bias. We developed a competitive reaching game (a variant of 'chicken game') in which aiming for greater rewards increased the risk of no reward and subjects competed for total reward with their opponent. The game resembles situations in sports, such as a penalty kick in soccer, service in tennis or the strike zone in baseball. In three different experiments, we demonstrated that, at the beginning of the competitive game, the subjects robustly switched their risk-seeking strategy to a risk-averse strategy. Following the reversal of the strategy, the subjects achieved optimal decision-making when competing with risk-averse opponents. This optimality was achieved by a non-linear influence of the opponent's decisions on the subject's decisions. These results suggest that interactions with others can alter motor decision strategies and that competition with a risk-averse opponent is the key for optimising motor decision-making.

Introduction

Optimal decision-making is indispensable for ideal performance in sports and fine motor control in everyday life. For example, selecting an appropriate trajectory for reaching a glass of water can lead to a low risk of spilling water, and likewise, finding a running course to easily pass through in rugby and deciding the best aiming location in a tennis match can increase the possibility of victory in a competition. Despite the importance of optimal decision-making, for over a decade, sub-optimal and overly risk-seeking behaviours have been

reported in various motor decision tasks[1-9]. Determining how to improve sub-optimal and risk-seeking decision-making behaviour is crucial to enhance well-being in daily life and performance in sports. However, how motor decision-making can be optimised remains unknown.

A possible solution to achieve optimal decision-making is interactions with other people. It has been shown that the observation of other people's movements induces synchronisation in one's own movement speed during a competitive game[10], facilitates movement adaptation[11], and influences the prediction of other people's movement[12]. Since risk-seeking behaviour has been reported in motor tasks in which subjects perform alone, the presence of other people may influence sub-optimal motor decisions.

Here, we investigated how humans alter their motor decision-making in a competitive game (a variant of 'chicken game'), which requires naturalistic interactions with other people. We had two main hypotheses. First, if the decision system simply imitates an opponent's movement, then a linear relationship between the subject's and opponent's decisions should be observed. If this is correct, optimal decisions should be achieved when the opponent's decisions are also optimal. This hypothesis is based on evidence that the unintended imitation of movement speed or distance occurs in a competitive situation[10]. Second, if the decision system adaptively changes the motor plan based on the opponent's movements, then a non-linear relationship should be observed. If this hypothesis is true, optimal decisions should be achieved when the opponent's decisions are sub-optimal.

To test these hypotheses, we assessed subjects' behaviour during competition with a virtual opponent who behaved either optimally or sub-optimally. First, we show that the direction of the sub-optimality of motor decisions is reversed from risk-seeking to risk-averse in the beginning of the competitive situation. Second, following this reversal of sub-optimality, we

demonstrate that competition with sub-optimal risk-averse opponents promotes optimal decision-making. Finally, to explain these findings, we confirm that the subjects' decisions are affected by opponents' decisions in a non-linear function.

Results

Subjects performed a quick out-and-back reaching task (moving forward from the start position and returning to the start) using a pen-tablet (Fig. 1a,b). A cursor corresponding to the position of a digitised pen was presented on a vertical screen. The endpoint of each movement was defined as the maximum y-position (Fig. 1b), and the subjects were rewarded depending on the endpoint following an asymmetric gain function in each trial (Fig. 1c). The subjects scored more points if the endpoint was located closer to the green boundary line (set 30 cm forward from the start position); however, if the boundary line was crossed, the score was set to 0. The nature of this game resembles several situations in sports, such as a penalty kick in soccer, service in tennis or the strike zone in baseball. The subjects could aim at any point on the screen. For the selected aim point, the actual endpoint was probabilistic due to the inherent noise of the motor system. Therefore, the subjects were required a continuous motor decisions regarding where to aim considering this inherent motor noise.

Two tasks were used: an individual task requiring the subjects to maximize the total score within each block (10 trials/block) and a competitive task requiring them to take a higher total score than their opponents within each block. In Experiment 1, the subjects were randomly divided into three groups: *risk-neutral*, *risk-averse* and *individual groups*. In the risk-neutral group, the subjects (N = 9) competed against virtual opponents whose aim points were set to the optimal aim point (see Design and Procedure). The optimal aim point was calculated by maximising the expected gain based on each subject's endpoint variability over the past 40 trials

before starting each block of the competitive task (see Model assumption). Because the subjects' endpoint variability decreased with the progression of the block, risk-neutral opponents' aim points gradually increased (red line in Fig. 4a). In the risk-averse group, the subjects (N = 8) competed against the opponents who gradually changed their aim point from optimal to sub-optimal and risk-averse (red line in Fig. 4b). The opponents' actual endpoint varied from trial to trial and followed a Gaussian distribution.

Three experimental sessions were performed. The subjects in the risk-neutral and risk-averse groups performed 5 blocks of the individual task (baseline), 12 blocks of the competitive task (competition) and 5 blocks of the individual task (washout). In the individual group, the subjects (N = 10) performed the individual task for 22 blocks. Based on Bayesian decision theory[13-15], we determined each subject's risk-sensitivity in the individual (baseline) and competitive task as the deviation of the actual aim point (observed mean endpoint) from the optimal aim point (see, Model assumptions). If the actual aim point was larger than the optimal aim point (i.e. a positive value), it indicated that the subject adopted a sub-optimal, risk-seeking strategy (seeking a high one-trial reward with a high probability of failure). In contrast, if the actual aim point was smaller than the optimal aim point (i.e. a negative value), it indicated a sub-optimal, risk-averse strategy (seeking a low one-trial reward avoiding high probability of failure). If risk-sensitivity was close to 0, the subject was considered to have made optimal, risk-neutral decisions.

Figure 2a and b illustrate the time series of the reaching endpoint from the baseline to competition. A comparison of the actual and optimal aim points revealed that the subjects adopted a risk-seeking strategy at the baseline (Fig. 2a',b'); however, they shifted their strategy to be risk-averse by decreasing the reaching endpoint from the baseline at the beginning of the competition (Fig. 2a,a',b,b'). This shift in strategy—a significant decrease in endpoint from

mean endpoint (actual aim point) at the baseline—was found in the first several trials of the competitive task (Fig. 2a,a',b,b'; 1st and 4th trial in the risk-neutral group: *ts* [8] > 2.42, *ps* < 0.042, *ds* > 1.07, mean differences = 1.44 and 0.92, 95% CIs = [0.53, 2.35] and [0.04, 1.80], respectively; 1st and 2nd trial in the risk-averse group: *ts* [7] > 2.63, *ps* < 0.034, *ds* > 1.34, mean differences = 1.91 and 2.05, 95% CIs = [0.20, 3.62] and [0.74, 3.35], respectively). This effect was seen neither when the subjects continued the individual task (Fig. 2c,c') nor during the period from competition to washout (Supplementary Fig. 1a,a',b,b'). Although the risk-seeking strategy was robust even after repetitive practice for 9 days[6], our results indicated that it could be switched to a risk-averse strategy when competing with a novel opponent. In other words, interactions with other people significantly altered motor decision-making.

We further validated this reversal of risk-sensitivity using additional experiments. Since human motor control is influenced by both intrinsic uncertainty of the motor system[16] and the extrinsic uncertainty of the environment[17,18,19], we attempted to attenuate these uncertainties before starting the competition. The subjects in the individual group from Experiment 1 performed the competitive task with risk-neutral opponents after completing 22 blocks of the individual task. This practice reduced intrinsic uncertainty: the SD of the reaching endpoint for the last five blocks was 0.73 times lower than that for the first five blocks. In Experiment 2, a new group of 11 subjects was recruited (presentation group). To attenuate the extrinsic uncertainty of the opponents' behaviour, the subjects were shown the movement of the risk-neutral opponents for 10 trials prior to starting the competitive task. Although the subjects improved reaching accuracy or knowledge of their opponents in advance, the reversal of risk-sensitivity (from risk-seeking to risk-averse) occurred at the beginning of the competitive task (Fig. 2d,d',e,e'; 1st, 2nd, 3rd and 5th trial in the individual group: *ts* [9] > 2.65, *ps* < 0.027, *ds* > 1.06, mean differences = 2.39, 0.88, 0.74 and 0.77, 95% CIs = [1.37, 3.40], [0.24, 1.52],

[0.15, 1.33] and [0.11, 1.43], respectively; 1st, 2nd and 3rd trial in the presentation group: *ts* [10] > 2.82, *ps* < 0.018, *ds* > 0.78, mean differences = 2.53, 1.82 and 0.70, 95% CIs = [1.17, 3.89], [1.02, 2.63] and [0.15, 1.26], respectively). We hypothesised this bias was triggered by virtual competition with the computer opponent. To test this, we recruited 14 pairs of subjects (human vs. human group) for Experiment 3. A (preceding) subject first performed the first trial of the competitive task, and then, the other (following) subject performed the first trial. Each pair repeated these tasks for 10 trials and competed for a higher total score. When two subjects competed with each other, a similar trend (decrease of endpoint from the baseline) was observed (Fig. 2f,f' and Supplementary Fig. 2a,a'; 1st, 2nd and 3rd trial in the preceding subjects: *ts* [13] > 2.51, *ps* < 0.026, *ds* > 0.95, mean differences = 1.08, 1.10 and 0.95, 95% CIs = [0.40, 1.76], [0.18, 2.03] and [0.13, 1.77], respectively; 1st, 2nd, 3rd and 5th trial in the following subjects: *ts* [13] > 2.22, *ps* < 0.045, *ds* > 0.74, mean differences = 2.59, 1.60, 0.64 and 0.99, 95% CIs = [1.50, 3.68], [0.87, 2.32], [0.02, 1.26] and [0.21, 1.77], respectively). Taken together, these findings suggest a clear tendency to abandon an original risk-seeking strategy and start a competition in a conservative manner even when the intrinsic and extrinsic uncertainties are attenuated or when competing against a human opponent.

Following the reversal of risk-sensitivity at the onset of the competitive task, we investigated the influence of the opponents' decision-making on the subjects' risk-sensitivity. Again, the risk-seeking strategy (positive value of risk-sensitivity) was adopted at the baseline in the three groups (Fig. 3), which remained the same in the individual group (Fig. 3 magenta; two-tailed one-sample *t*-test from 0: 1st to 12th block, *ts* [9] > 3.07, *ps* < 0.013, *ds* > 1.50, mean differences = 1.32, 1.01, 0.72, 0.84, 0.85, 0.86, 0.75, 0.96, 0.62, 0.86, 0.69 and 0.86, 95% CIs = [0.77, 1.86], [0.41, 1.62], [0.27, 1.17], [0.32, 1.35], [0.61, 1.09], [0.31, 1.42], [0.31, 1.18], [0.44, 1.48], [0.16, 1.07], [0.49, 1.22], [0.36, 1.02] and [0.46, 1.25], respectively). However, the

risk-seeking strategy partly improved to be risk-neutral when competing against a risk-neutral opponent (Fig. 3 green; two-tailed one-sample *t*-test from 0: 2nd, 3rd, 8th and 12th block, *ts* [8] > 2.34, *ps* < 0.047, *ds* > 1.17, mean differences = 0.48, 0.68, 0.44 and 0.49, 95% CIs = [0.01, 0.96], [0.22, 1.13], [0.22, 0.67] and [0.10, 0.89], respectively). Specifically, when the opponent was risk-averse, the optimal risk-neutral strategy was achieved for all blocks of the competitive task except the first block (Fig. 3 blue; two-tailed one-sample *t*-test from 0: 1st block, *ts* [7] > 2.61, *ps* < 0.035, *d* = 1.39, mean difference = 0.44, 95% CI = [0.04, 0.83]). Furthermore, two-way mixed design ANOVA revealed a significant group × block interaction (F [22, 264] = 2.12, p = 0.002, η^2 = 0.09). The risk-sensitivity values in the risk-averse group were significantly smaller than that in the individual group in blocks 7, 8, 9 and 10 (Supplementary Fig. 3; *ps* < 0.05, Bonferroni correction). No significant differences were observed among the three groups in terms of the SD of the reaching endpoint or optimal aim point (Supplementary Fig. 4a,b). These results indicated that the sub-optimal risk-seeking strategy was modified by the presence of the opponent. Specifically, the optimal risk-neutral strategy was promoted by competition with a sub-optimal risk-averse opponent.

Next, we addressed why the competition with sub-optimal risk-averse opponents led to optimal and risk-neutral decision-making. To specify the relationship between the opponents' and subjects' decisions, we calculated the following indices as measures of motor decision-making: A_i, mean endpoint across five blocks in the individual task, A_c, mean endpoint across each block in the competitive task and A_o, opponents' mean endpoint across each block in the competitive task. The subjects in the risk-neutral group gradually increased their aim point as the opponents' aim point increased (Fig. 4a; r = 0.82). In contrast, there was no such correlation in the risk-averse group, and the subjects maintained their aim point even though the opponents' aim point decreased (Fig. 4b). When repeating the individual task, a

significant increase in the aim point was observed over 12 blocks (Fig. 4c; main effect of the block in one-way within-subject ANOVA: F [11, 99] = 2.74, p = 0.004, η^2 = 0.23). To further explore this relationship, the subjects' relative aim points (defined as $A_c - A_i$) in the two competitive groups were plotted against the opponents' relative aim points (defined as $A_o - A_i$), as shown in Figure 4d. If the opponents' decisions linearly influenced the subjects' decisions, the slopes of regression line across the right and left halves of the plot should be similar. If this linear relationship is valid, subjects should make optimal decisions when the opponents make optimal decisions. In contrast, if the opponents' decisions non-linearly influence the subjects' decisions, the slopes should be different. If this non-linear relationship is valid, the subjects should make optimal decisions when the opponents make sub-optimal decisions. As shown in Fig. 4d, we found a gentler slope in the left half of the plot than in the right half of the plot. To assess the statistical difference, we calculated the slopes of regression lines in bootstrapped samples (Fig. 4e). The mean slopes were 0.21 (95% CI = [0.07, 0.35]) for the left half of the plot and 0.63 (95% CI = [0.41, 0.83]) for the right half of the plot, which were significantly different (Fig. 4e; permutation test: p < 0.001). These results suggest that the subjects' decision-making was influenced by a non-linear function of the opponents' decision-making—competition with sub-optimal, risk-averse opponents led to optimal decision-making—.

Discussion

For over a decade, sub-optimal and risk-seeking behaviours have been repeatedly confirmed in studies of motor decision-making tasks with an asymmetric gain function[4,5,6,8], that require a choice with different variances of pay-off [2,3,7,9] and involve a speed-accuracy trade-off [1]. Despite such findings, solutions to promote optimal motor decision-making are lacking. Here,

we assessed the potential effect of interaction with opponents on sub-optimal motor decision-making with a prediction that other people's actions/intentions can influence the subjects' motor system[10,11,20,21]. First, we found that the subjects' risk-seeking strategy in the individual task reversed to risk-averse strategy at the very beginning of the competitive task (Fig. 2). Second, optimal motor decisions were promoted by competition with a risk-averse opponent (Fig. 3). This optimal decision-making was induced by a non-linear influence of the opponents' decisions (Fig. 4).

The reversal of risk-sensitivity was robustly shown through several experiments (Fig. 2). However, this switching of strategy from the individual task is irrational. In the individual task, the subjects were instructed to maximise the total score. At the beginning of the competitive task, when the subjects did not know the opponent's strategy, they should have maintained their original strategy to maximise the total score and beat the opponent. The data showed large decrease in endpoint in the first trial, and it recovered thereafter (Fig. 2). A possible explanation for this behaviour is that the subjects sought a better strategy believing that they would compete against a weak opponent who aimed for a lower score. If the subjects believed that the opponent was strong and would aim for a higher score, they would have never changed their original strategy. Therefore, this amount of decrease reflects the subjects' risk-premium[22] that they would recover the points in later trials even if they scored fewer points at the beginning. By scarifying the cost of scoring fewer points, the subjects may be seeking an optimal strategy to beat a weak opponent.

We also found that the subjects' motor decisions were non-linearly influenced by the opponents' decisions (Fig. 4). The subjects increased their aim point when the opponents also aimed for a higher score (Fig. 4a). In contrast, when the opponents aimed for a lower score, the subjects did not change their aim point (Fig. 4b). Therefore, the subjects adaptively altered their

decisions according to the opponents' decision, rather than imitating it. If the opponents' decision linearly affected the subjects' decision and imitation occurred, the subjects would have also aimed for a lower score. The decision strategy that the subjects adopted can be interpreted as a variant of the win-stay lose-shift strategy[23]. Importantly, in terms of the win-stay part (Fig. 4b,d), the subjects decreased their aim point from the individual task and then let the strategy 'stay', rather than adopt the original risk-seeking strategy and then let the risk-seeking strategy 'stay'. These inhibitory and non-linear effects of the opponents' decision induced the subjects to make optimal and risk-neutral decisions. Further research is necessary to clarify how the opponent was modelled in the decision system to generate an optimal motor plan.

Strategic decision-making has been investigated in game theory tasks that require players to make discrete choices[24]. In the Prisoner's Dilemma game[25]—a standard game theory task—two prisoners have two choices, cooperation or defection, which determine four possible pay-offs (prison sentences). In the current study, however, the subjects decided where to aim to beat their opponent. Such continuous choice (motor decision-making) is often required in competitive sports (soccer, tennis, baseball, golf, darts, etc.). The current study, therefore, highlighted the characteristics of movement strategy in competitive situations. Specifically, we clarified how interaction with opponents improved sub-optimal motor decision-making. When humans practice a motor task alone (without opponents), repetitive practice has been shown to improve movement accuracy but not movement strategy[6]. Our findings suggest that competition with an opponent, particularly a risk-averse opponent, is an effective means to promote an optimal and risk-neutral movement strategy. In behavioural economics, Richard Thaler (Nobel economics winner in 2017) proposed 'nudge' as a means of behavioural change since human decision-making is systematically biased under bounded rationality (nudge refers to the choice architecture which guides people's choice toward a beneficial one while maintaining freedom of

choice)[26]. The presence of other people can be interpreted as one of the nudges which alter sub-optimal motor choice. This information may be helpful for sports trainers and coaches to achieve a better motor performance—the importance of other people should be considered in developing a training protocol in sports.

Methods

Subjects

We recruited 66 healthy adults (41 males; 18–24 years) for the experiments. Experiment 1 comprised three subgroups with 9 (3 males; 20.4 ± 2.7 years), 8 (5 males; 19.1 ± 0.6 years), and 10 (7 males; 19.9 ± 2.0 years) subjects assigned to the risk-neutral, risk-averse, and individual groups, respectively. Eleven subjects (10 males; 20.2 ± 2.1 years) participated in Experiment 2 (presentation group), and 14 pairs of subjects (16 males, 12 females; 21.2 ± 2.0 years) participated in Experiment 3 (human vs. human group). This study was approved by the ethics committee of Tokyo University of Agriculture and Technology and was carried out in accordance with the approved guidance. Subjects provided written informed consent and were unaware of the purpose of the experiment.

Apparatus

We used a pen-tablet with sufficient workspace to measure the subjects' arm-reach movement (Wacom, Intuos 4 Extra Large; workspace:, 488 × 305 mm). The subjects made a quick out-and-back reaching movement holding the digitised pen on the pen-tablet (Fig. 1a). The position of the digitised pen was sampled at ~144 Hz with a spatial resolution of 0.01 mm. The subjects manipulated a cursor on a vertical screen whose position was transformed from the pen position with a maximum delay of 69 ms(Asus, VG-248QE; size: 24 inches, refresh rate:

~144 Hz). The scale of the pen and cursor position was 1:1. All stimuli were controlled using Psychophysics Toolbox[27,28].

Experimental task

There were three tasks: *training task*, *individual task* and *competitive task*. For all tasks, to begin each trial, subjects moved a blue cursor (radius: 0.3 cm) to a white starting position (radius: 0.4 cm) presented on the vertical screen. After a 1-s delay, a horizontal white line (width: 0.1 cm) appeared 30 cm from the starting position and turned green after random intervals of 0.8–1.2 s, indicating the 'go' signal. In this paper, this green line is referred to as the 'boundary line'. After the 'go' signal, the subjects made a quick out-and-back reaching movement to rapidly move the cursor forward and then return it below the starting position. The subjects received the online feedback about how the cursor was moving, but could not see their own hand position since it was covered with a box. We recorded the endpoint of each movement as the maximum y-position (Fig. 1b). If the subjects did not return the cursor within 600 ms (time-out), a message stating 'Time-out. More quickly!' was presented with a warning tone. If the subjects successfully completed the trial, a yellow cursor (radius: 0.3 cm) appeared at the position of the reaching endpoint for 2 s. After the feedback period, the subjects proceeded to the next trial.

Training task

Before the individual task, a training task was performed to allow the subjects to practise the reaching movement. The subjects were required to reach the green boundary line. After each movement, if the yellow cursor overlapped with the green boundary line, the

message ‘Hit!’ appeared on the screen with a pleasant sound. The training task comprised 50 trials.

Individual task

In the individual task, the subjects were awarded points depending on the reaching endpoint (Fig. 1c). More points were awarded when the endpoint was closer to the green boundary line at 30 cm; however, the score for this trial fell to 0 if the endpoint crossed the boundary line. When a mistrial occurred a ‘Miss!’ message appeared on the screen with a flashing red lamp along with an unpleasant alarm. Of note, 0 points were also awarded if the endpoint was within 7 cm of the start, but no such trials were observed. In case of time-out, 0 points were also awarded. In the feedback period, the current points and total points were presented along with the reaching endpoint. The subjects were instructed to maximise the total points in each experimental block, comprising 10 trials each.

Competitive task

In the competitive task, the subjects performed the task against a computer opponent (Experiments 1 and 2) or a human opponent (Experiment 3). Each experimental block comprised 10 trials. When it was the subject’s turn, they performed the reaching movement in the same way as in the individual task. After the feedback period, a red cursor (radius: 0.3 cm) was shown on the screen, indicating the opponent’s turn. In the competitive task with the computer opponent, the opponent’s cursor movement (trajectory) was automatically manipulated based on pre-recorded sample trajectories made by the experimenter. Each movement endpoint was determined by the pre-programmed algorithm described below (Design and Procedure). In the competitive task with a human opponent, two sets of pen-tablet and

screen were prepared. The same stimuli were presented on each screen. A vertical partition was used to separate the two subjects, preventing verbal and non-verbal communication during the experiment. In the competitive task, the subjects were instructed to win the game by achieving a higher total score than their opponents at the end of each experimental block.

Design and Procedure

For the risk-neutral and risk-averse groups in Experiment 1 and Experiment 2, there were three experimental sessions: *baseline* comprising 5 blocks of the individual task, *competition* comprising 12 blocks of the competitive task and *washout* comprising 5 blocks of the individual task. For the individual group in Experiment 1, there were 22 blocks in the individual task and 4 blocks in the competitive task. In Experiment 2 (presentation group), the subjects observed the movement of the computer opponent for 10 trials before performing the competitive task. In Experiment 3 (human vs. human group), there were *baseline* comprising 5 blocks of the individual task and *competition* comprising 12 blocks of the competitive task. Two subjects alternatively performed each block of the individual task. The subjects could not see each other's performances in the individual task. In the competitive task, two subjects performed the task alternatively from trial to trial.

For the computer opponent, we randomly sampled the endpoint of each trial from a Gaussian distribution with mean αE^* and variance σ^2, where α represents the coefficient that determines the opponent's risk-sensitivity and E^* represents the optimal mean endpoint maximising the expected reward given the variance of reaching endpoint σ^2. Before each experimental block in the competitive task, we determined the value of σ^2 by calculating the subject's reaching variance over the past 40 trials. This means that the computer opponent always had the same reaching accuracy as the subject. We then defined the computer's mean

endpoint as αE^*. We could dynamically manipulate the endpoint of the opponent by changing coefficient α. The value of α for the risk-neutral opponent was set as $\alpha = 1$ for all 12 experimental blocks, that is, the computer opponent always behaved as an optimal risk-neutral decision-maker who gradually aimed closer to the boundary line along with the reduction of the reaching variance. For the risk-averse opponent, this was set as $\alpha = 1$ for blocks 1–4, decreased in steps of 0.15 for blocks 5–8 and finally set as $\alpha = 0.925$ for blocks 9–12, that is, the computer opponent behaved as a sub-optimal risk-averse decision-maker who gradually aimed further from the boundary line. The differences in movements between the two computer opponents can be seen in Fig. 4 a,b.

Model assumptions

Based on Bayesian decision theory[13-15], we modelled the optimal mean endpoint by maximising the expected gain for a given sensory motor variability to quantify the subjects' risk-sensitivity and define the computer opponents' endpoint. In this model, the expected gain $EG(A)$ for a selected aim point A can be calculated by integrating the gain function $G(e)$ with the probability distribution of the movement endpoint $P(e|A)$.

$$EG(A) = \int_{-\infty}^{\infty} G(e) \cdot P(e|A) de \qquad (1)$$

We assumed that the actual movement endpoint e is distributed around a selected aim point A with sensory motor variability σ^2 according to Gaussian distribution.

$$P(e|A) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(e-A)^2}{2\sigma^2}\right] \qquad (2)$$

Given a subject's variability in movement endpoint σ^2, we estimated the optimal mean endpoint by maximising the expected gain function.

$$A^*(\sigma) = \underset{A}{\operatorname{argmax}}\, EG(A) \qquad (3)$$

To determine subject's risk-sensitivity in the individual (baseline) and competitive tasks, we calculated the mean endpoint (actual aim point) and the standard deviation of the endpoint for 5 blocks of the individual task and each block of the competitive task, respectively. To define the variance of reaching endpoint in the computer opponent, we calculated the subject's reaching variance over the past 40 trials before each block in the competitive task. For a detailed description of our model assumption, see Ota et al.[5,6].

Competing interests

The authors declare no competing interests.

Author's Contributions

KO and KT conceived and designed the experiments. KO performed the experiments. KO and KT analysed the data and interpreted the results. KO and KT wrote and revised the manuscript.

Acknowledgments

We thank Dr. Daichi Nozaki, Dr. Kazutoshi Kudo and Dr. Takuji Hayashi for inspiring discussions. This research was supported by Grant-Aid for JSPS Fellows No. 17J07822 and Hayao Nakayama Foundation for Science & Technology and Culture No. H29-B-58 awarded to KO and by JSPS KAKENHI No. 18K17894 awarded to KT.

Code availability

The code used to generate the data is available from the corresponding author on request.

Data availability

The data are available from the corresponding author on request.

Figures

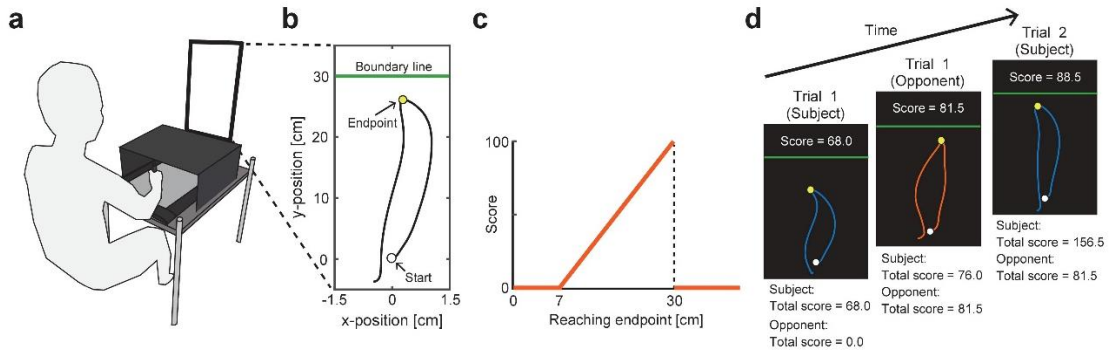

Fig. 1. Experimental set up (game of 'chicken').

a, Experimental apparatus. The subjects held a digitised pen on a pen-tablet. The stimuli were shown on a vertical screen in front of the subjects. **b,** Trajectory of reaching movement. The subjects made a quick out-and-back reaching movement, moving forward from an initial position (white circle) and returning to the initial position. The reaching endpoint (yellow circle) was calculated as the maximum y-position. **c,** Asymmetric gain function. The reaching endpoint determined the one-trial score. The maximum score (100 points) was associated with reaching the green boundary line (30 cm). **d,** Trial-sequence of the competitive task. The subjects and opponents performed the reaching movement in an alternating order. The current total scores for the subjects and opponents were presented on the screen at all times, indicating the difference in scores. The reaching trajectories (red and blue) were shown only for clarity.

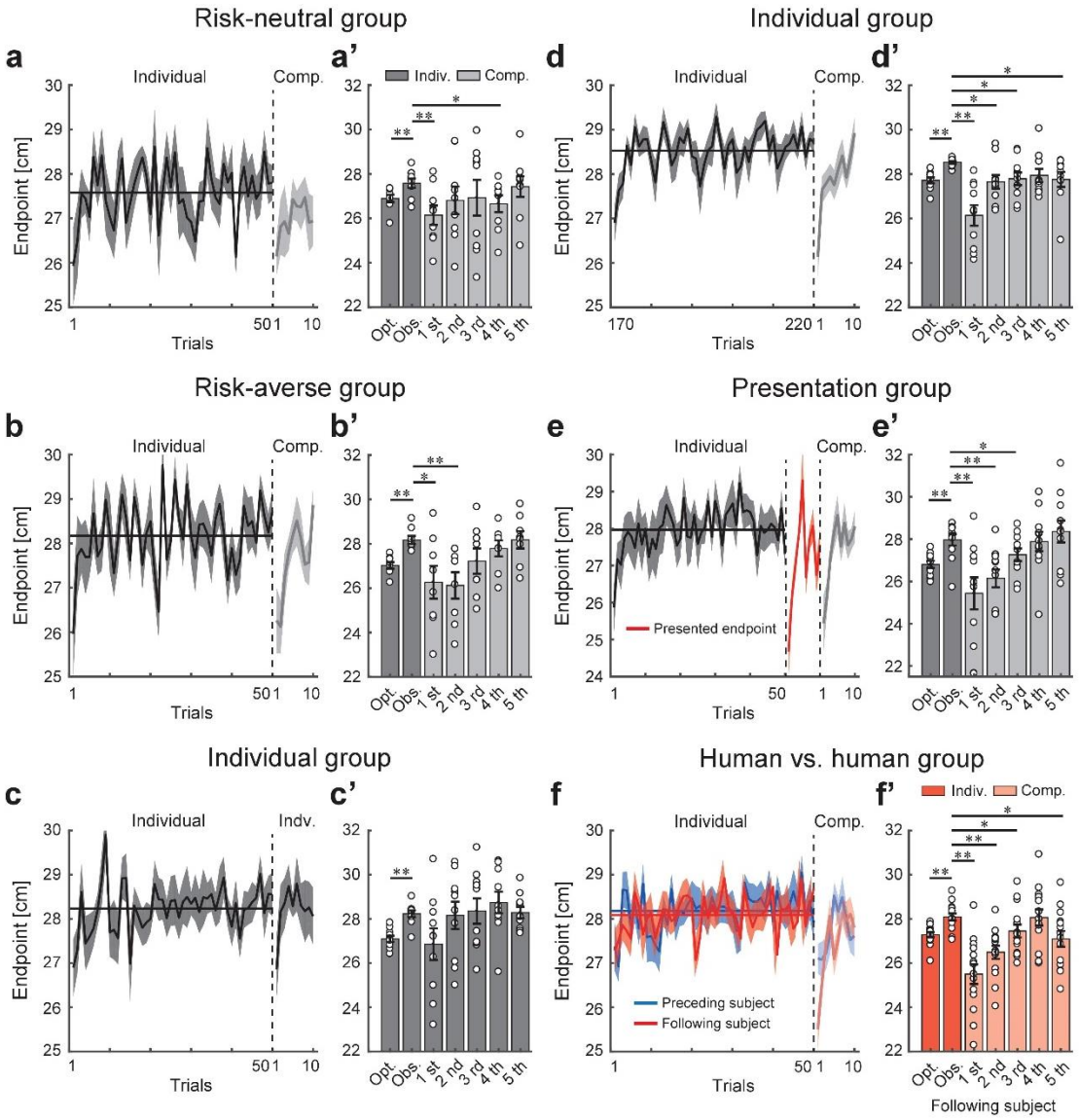

Fig. 2. Reversal of strategy from risk-seeking to risk-averse.

a-f, Time series of reaching endpoint. Data are averaged across the subjects and the shaded area denotes the SE of the mean. The horizontal solid line indicates the observed mean endpoint in the individual task (baseline) for 50 trials before the competitive task started **(a,b,d-f)** or when the individual task restarted **(c)**. **a'-f',** The bar graphs show the reaching endpoint. Data are averaged across the subjects, and the error bar denotes the SE of the mean. Opt. indicates the optimal mean endpoint in the individual task. Obs. indicates the observed mean endpoint in the individual task, which corresponds to the horizontal solid line in **(a-f)**. The average endpoints

are plotted from the first to fifth trials after the competitive task started **(a',b',d'-f')** or when the individual task restarted **(c')**. The horizontal lines above the bar graphs indicate statistically significant differences. * represents $p < 0.05$, and ** represents $p < 0.01$. Open circles denote individual subjects. In the preceding individual task, the risk-seeking strategy was adopted, indicated by the deviation from the optimal to the observed mean endpoint. However, the decrease in the endpoint was seen at the beginning of the competition **(a',b')**, suggesting that the subjects shifted their risk-seeking strategy to be risk-averse. This effect was robust even when the competitive task began after the individual task had been repeatedly performed **(d')**, when the opponents' endpoint was presented in advance **(e')** and when the subjects competed against human opponents **(f')**. When the subjects repeated the individual task, this strategy shift was not observed **(c')**.

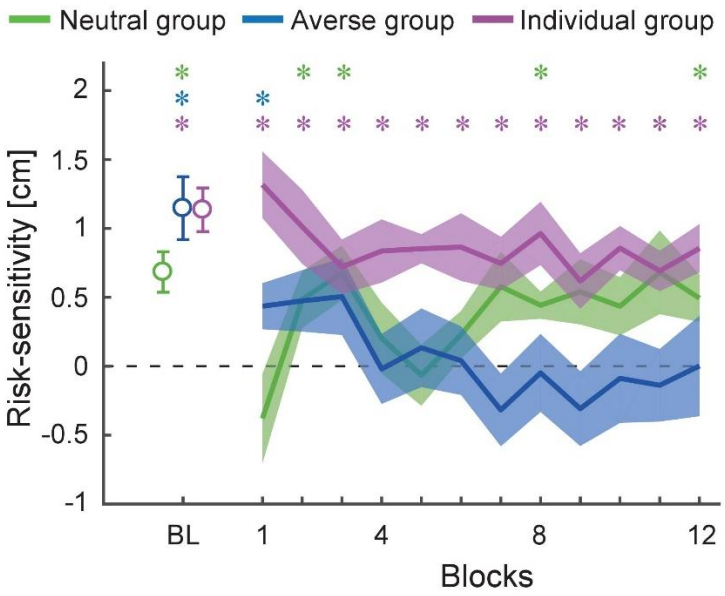

Fig. 3. Achievement of risk-neutrality influenced by the opponents.

Risk-sensitivity values, defined as the difference between the mean endpoint and optimal endpoint, were plotted for the individual task (baseline) and each block of the competitive task. Positive values indicate a risk-seeking strategy, and negative values indicate a risk-averse strategy. Green, blue and magenta asterisks denote $p < 0.05$ from the risk-neutral value (i.e. 0) for the risk-neutral opponent, risk-averse opponent and individual group, respectively. No asterisk indicates that the optimal, risk-neutral strategy was achieved. For the individual group, a consistent risk-seeking strategy was observed. This sub-optimal strategy partially improved in the risk-neutral group. In the risk-averse group, improvement in the risk-seeking strategy was observed in all blocks of the competitive task except for the first block. The group comparison of risk-sensitivity values is shown in Supplementary Figure 3.

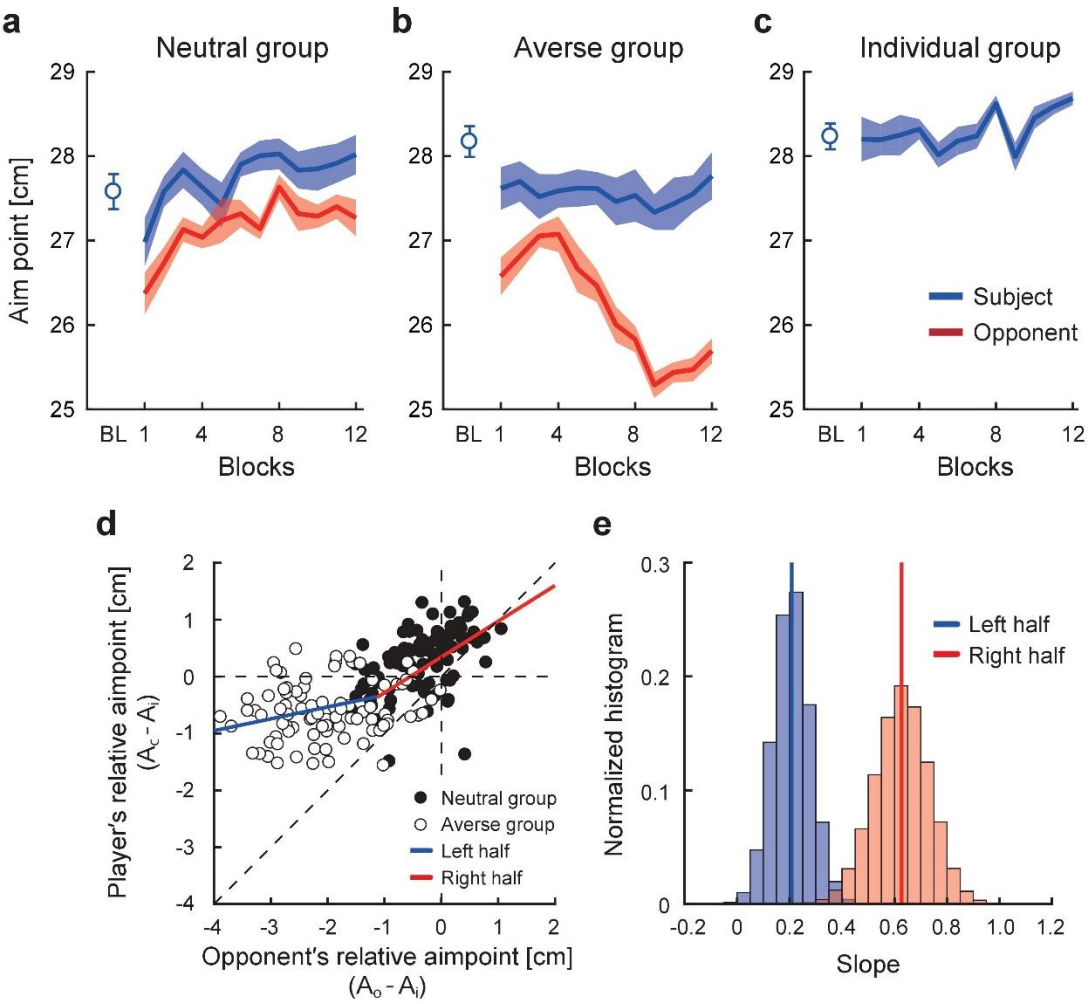

Fig. 4. Non-linear influence of opponent's decisions on subject's decisions.

a-c, Change of aim point (mean endpoint) when competing against a **(a)** risk-neutral opponent, **(b)** risk-averse opponent and **(c)** performing the individual task. Data are averaged across the subjects, and the shaded area denotes the SE of the mean. In the risk-neutral group, the subjects' aim points increased along with the opponents' aim points. In contrast, the subject's aim point in the risk-averse group did not change, whereas the opponents' aim points decreased. This non-linear relationship is clearly seen in **(d)**. **d**, Aim point modulation as a function of the opponents' relative aim point. The subjects' relative aim point (mean endpoint in the competitive task, A_c − mean endpoint in the individual task, A_i) is plotted against the

opponents' relative aim point (mean endpoint of the opponent, $A_o - A_i$). Black circles indicate the actual data of the risk-neutral group (11[2nd-12th] blocks × 9 subjects) and white circles indicate that of the risk-averse group (11[2nd-12th] blocks × 8 subjects). The slope of regression line in the left (blue) and right halves (red) of the plot predicted the non-linear influence of the opponents. **e,** Histogram of bootstrapped slopes of regression line (50000 repetition each). Vertical lines indicate the mean values of each distribution. Permutation tests revealed a significant difference between the slopes of regression lines, suggesting a smaller influence of the opponents' decisions on the subjects' decisions in the left half than the right half of the plot.

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