IS COMPETITIVE PRESSURE NECESSARY FOR LOSS-INDUCED RANDOM BEHAVIOR?

by

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Title: Is Competitive Pressure Necessary for Loss-Induced Random Behavior?

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Successfully navigating unfamiliar environments requires the ability to accurately update and apply a valid mental model of the environment to influence the next best move, and switch to other strategies if necessary. Recent research by Kikumoto & Mayr (2019) has shown that in competitive situations, humans employ model-based choice strategy following immediate positive feedback, but revert to random, stochastic choices following negative feedback. In this study, we attempt to recreate the results these authors found, but in a noncompetitive context. In one experiment measuring human subjects' likelihood to switch tasks based on positive or negative feedback, we find similar results; participants will make mental models of an unfamiliar situation and repeat an action when rewarded with positive outcomes, but revert to a stochastic choice strategy when faced with negative outcomes, suggesting that this phenomenon is a general cognitive strategy in navigating unfamiliar environments and not exclusive to competition alone.

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Introduction

Imagine a player competing in a game of soccer. Winning the soccer match requires the player to keep track of their opponent's actions, such as where they are on the field, where they are likely to kick the ball, and where they are likely to run to next. In addition, the player must keep track of their own actions as well; where should the player kick the ball? Where should the player run to? When people compete, there are two strategies employed: One can try to attempt to predict their opponent's behavior, and one can attempt to make themselves unpredictable (Mayr & Bell, 2008). Competition itself is a dance between exploitation and avoiding being exploited.

People's actions are influenced by recent actions and events in uncertain environments, suggesting a heavy reliance on learning and memory processes. One such basic, memory-based process is the perseveration effect as demonstrated in the voluntary task-switching paradigm (Arrington & Logan, 2004). When subjects were asked to randomly pick between two different tasks on repeated individual trials, these authors showed that rather than being able to make perfectly 50/50 random choices, people tend to repeat their previous choice with a probability of roughly 70%. Another learning and memory process frequently used is the win-stay/lose-shift tendency, or what is called a "memory-free choice," where people are likely to repeat a previous action when rewarded with positive feedback but switch to a different choice when receiving negative feedback (Forder & Dyson, 2016).

When competing, a soccer player might also try to imagine what their opponent is going to do next and use their beliefs about their opponent's strategies to influence their next move. This example of using recent events or observations in one's environment to influence their next executed action is considered a model-based decision (Lee, Shimojo, & O'Doherty, 2014), often regarded as the most sophisticated use of our internal representations to guide upcoming actions.

Yet, using model-based or memory-based choices can introduce regular patterns into players' behavior that opponents in competitive situations may exploit. Likewise, given humans' working memory limitations, it is difficult to consistently update and apply a valid model of an opponent. It is a natural conclusion, therefore, that when memory-based or model-based influences do not result in successful choices, people should be able to "turn off" these strategies and rely on a randomly selected choice process to determine their next action. At the very least, such random choices would be unpredictable to the opponent.

Previous work by Kikumoto and Mayr (2019) has demonstrated that people use model-based choices when rewarded with positive outcomes, but switch to a stochastic, unpredictable strategy after negative outcomes. The authors studied human subjects with a variant of the matching-pennies game, giving the participants one of two roles: They could either attempt to match their opponent's next move (the "fox" role), or attempt to choose the opposite of the opponent's next move (the "rabbit" role). The critical experimental manipulation consisted of varying the rate in which the opponents switched their own choices from trial to trial, providing a very clear empirical criterion for when people are using a model-based strategy and when they are behaving unpredictably (Figure 1). It was expected that participants receiving positive feedback should be specifically contingent with matching the switch rate of the opponent when using a valid model of said opponent, whereas the opposite pattern should emerge following participant losses (i.e., the player should switch often when the opponent switches rarely and vice versa). In contrast, when participants behaved unpredictably, it was expected that they should switch choices over or around 50% of the time, and be unaffected by the switch rate of the opponent.

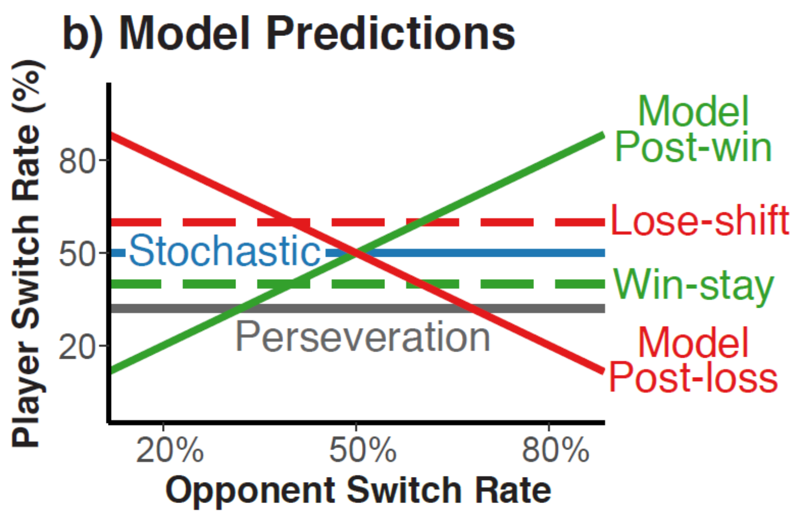

Figure 1.

Figure 1b from Kikumoto & Mayr's (2019) hypothesis of model-based choice after wins and memory-free choice after losses predicted that player's strategies would show a positive linear interaction between opponent switch rate and player switch rate after wins, and a negative linear interaction between opponent switch rate and player switch rate after losses. Additionally, they predicted a 50% player switch rate unrelated to the opponent's switch rate after memory-free choices. The perseveration bias was predicted to lead to an overall debasement of switch rate, and a win/stay-lose/shift increase for post-loss trials, and a decrease post-win trials (Kikumoto & Mayr, 2019).

Figure 1 also shows how the other memory-based phenomena, namely the perseveration and win-stay/lose-shift bias, were predicted to manifest in participants' switch rates. Results indeed showed that participants behaved in a model-based manner following positive feedback, but reverted to much more random, stochastic choices following negative feedback (Figure 2). In addition, perseveration and win-stay/lose-shift biases were detected in the results.

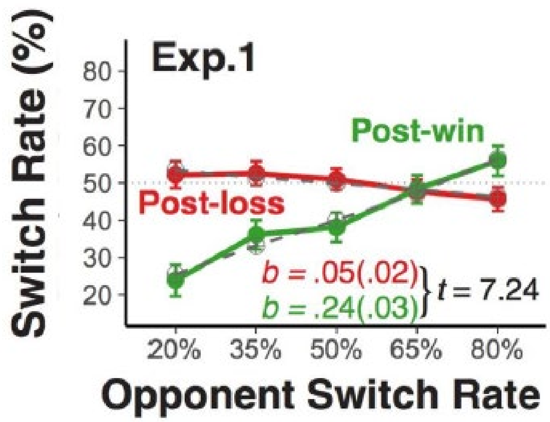

Figure 2.

Kikumoto & Mayr (2019) showed average switch rates for post-win and post-loss trials as a function of the computerized opponents' switch rates. The analysis included a regression of the player switch rate on the opponent switch rate. These results tended to follow the predicted model, with a positive linear interaction between player switch rate and opponent switch rate post-win, and a negative linear reaction between player switch rate and opponent switch rate post-loss.

While this previous work provides strong evidence that in competitive situations there is a clear distinction between model-based and unpredictable, random decisions, it is not clear to what degree competition itself is a necessary condition for this pattern to emerge. It is an important question whether the feedback-based toggling between model-based and random behavior is constrained to competitive situations, or instead is a much more general feature of choice behavior in uncertain environments. One might argue from a theoretical perspective that even in the absence of explicit competition, it may be useful for failure to trigger a restart so that the organism may explore the full range of possible moves.

There are also empirical reasons for suspecting that this observed phenomenon is not limited to competitive situations alone. Hermoso-Mendizabal et. al (2020) studied rats performing a two-choice auditory discrimination task, where the probability of stimulus repetition was modulated in blocks of trials, much like the switch rate of opponents in Kikumoto and Mayr (2019). The rats learned expectations about upcoming stimuli, as the task was designed to mimic regular timed events in an ecological environment, based on changes in the stimulus sequence. Similar to the results found in human participants, the rats also created mental models of their unfamiliar situation, and repeated or alternated their responses based on previous positive outcomes. The rats also reverted to random behavior after negative outcomes. Given the lack of competition in the task, the fact that rats showed this behavior pattern suggests that this choice strategy is general and not limited to competitive situations.

Therefore, in the current study, we attempt to recreate the results of Kikumoto & Mayr (2019) in human participants in an exclusively non-competitive context. Upon finding a pattern of model-based choice following positive feedback, but stochasticity following negative feedback, we can rationally conclude that this mixed model-based/random strategy is indeed a general feature of choice under certainty.

Methods

Participants (*N* = 53) were University of Oregon students paid $10.00 per hour with an opportunity to earn an additional $0.02 per trial. The University of Oregon's Human Subjects Review Board approved the study protocol. In accordance to the experiments used by Kikumoto and Mayr (2019), methods of data collection were modeled after the voluntary task-switching paradigm, with an identical task with different instructions modified to omit competitive context. Words like "win," "lose," or "game" were excluded. Instructions for the task asked participants to try to figure out the computer's "rule" that decided on whether or not they earned $0.02 per trial based on their responses within individual trials, and based on a probabilistic rule that, unbeknownst to the participant, mimicked the "opponent" component of the Fox and Rabbit styled matching penny task.

In every trial, the participant was faced with a white rectangular frame that appeared in the center of the screen. A red dot would randomly appear at either the top or bottom of the frame and would start shrinking once present. The participant would have to make their decision before the dot disappeared. The options were to keep the position of the dot or move it, using the spatially corresponding key on the number pad. Task instructions mentioned that the computer was deciding on whether or not the participant earned an extra $0.02 per trial, and it was up to the participant to guess this probabilistic rule. The participants completed 10 blocks of 80 individual trials. In the non-competitive task, the participant was simply trying to figure out how to earn more money, instead of competing against the computer and trying to win.

The degree to which participants used a model of their opponent was measured by exposing players to differing frequency shift rules, (i.e., the computerized opponents in Kikumoto & Mayr's task) with varying average switch rates of 20%, 35%, 50%, 65%, and 80%. Exactly like Kikumoto and Mayr (2019), as the participants kept or moved the position of the dot appearing in the frame on every trial, they were given instant feedback on whether or not they did or did not earn money (Figure 3). Measuring the participant's switch-rate variations give a clear behavioral diagnostic of both model-based and memory-free behavior.

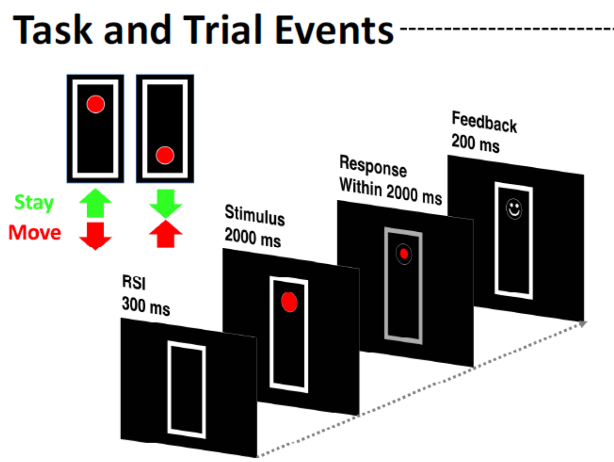

Figure 3.

Data collection task and trial events: Participants were given instant feedback on wins or losses after choosing to move or keep the position of a circle that randomly appeared at the top or bottom of a rectangular frame. Instead of framing the task as a competition between the participant and a computerized opponent, the participant was tasked with guessing the "rule" the computer was using to decided whether or not to reward them with $0.02 per trial.

Results

As in Mayr and Kimumoto (2019), participants' rate of switching their own choices from one trial to the next was the main dependent variable.

Before testing the main prediction with a repeated measures ANOVA, we selectively inverted the labels for the computer modulated switch rate in the post-loss trials (e.g, 20% becomes 80%). Failure to do so would simply compare the slopes of the post-win and post-loss switch rate functions. This would not differentiate between a pattern of post-loss and post-win functions with the same slope but opposite signs, and the predicted pattern of more shallow slopes following losses.

A significant main effect of previous trial outcome on player switch rate was found such that when players won in the previous trial ($M = 0.422$, $SD = 0.494$), they were likely to repeat their previous choice. However, when players lost on previous trials, they were likely to revert to stochastic, random behavior ($M = 0.614$, $SD = 0.487$), $F(1, 52) = 130.98$, $p<0.001$ (Tables 1 & 2). Figure 4 shows the switch rate as a function of the opponent's switch rate and win-versus-loss feedback. As apparent from the figure, the switch rate increases linearly as a function of opponent's switch rate following win feedback, indicating model-based choice. If people were behaving in the same model-based manner following losses, they would demonstrate a similarly steep switch rate function, just in the negative direction. Instead, we see a more shallow function here, indicating that people chose in a largely random manner. Overall, this pattern closely replicates the pattern of results that Kikumoto and Mayr have obtained in a competitive environment.

Trial Outcome	*M*	*SD*
Loss	0.614	0.487
Win	0.422	0.494

Table 1. Effect of Previous Trial Win or Loss on Participant Switch Rate

Descriptive statistics of trial outcome on participant switch rate.

Effect	*DFn*	*DFd*	SSn	SSd	F	p	p <.05	ges
WIN/LOSS	1	52	6.049	2.402	130.976	0	*	0.526
MODEL	1	52	4.077	1.741	121.773	0	*	0.426
WIN/LOSS:MODEL	1	52	1.326	1.317	52.3346	0	*	0.195

Table 2. Linear Main Effect on Participant Switch Rate Categorized by Computer Switch Rate

Descriptive statistics of computer switch rate (categorized by 20%, 35%, 50%, 65%, and 80%) on participant switch rate.

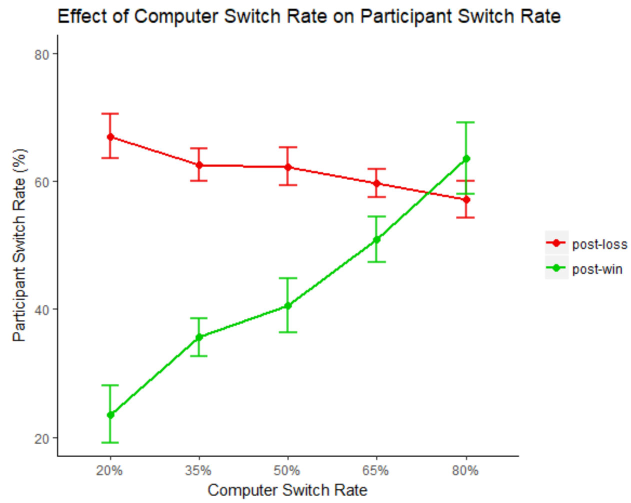

Figure 5.

Average empirical switch rates for post-win and post-loss trains as a function of computerized "opponents'" switch rates. As a test of these interactions, we show the corresponding means (SD); green = post-win, red = post-loss. At computer switch rates 20%, 35%, 50%, 65%, and 80%, participant switch rates were 0.388 (SD = 0.487), 0.489 (SD = 0.5), 0.520 (SD = 0.5), 0.562 (SD = 0.496), and 0.626 (SD = 0.484), respectively.

It is noteworthy however that there are also differences to the past results. Specifically, whereas in Kikumoto and Mayr, switch rates following losses hovered around 50%, they were substantially higher in the current experiment. On average, the contrast between win trials and loss trials was nearly 20% (see Table 1), indicating that in this experiment the win-stay/loss-shift bias was particularly strong. It is possible that the absence of opponents strengthens this reward-based strategy, perhaps because players here need to worry less that such strategy would be exploited by a clever opponent. Overall, however these results clearly demonstrate the generality of the mixed model-based/random strategy beyond the competitive context.

Discussion

The question we tried to answer in this research is to what degree a previous observed strategy of feedback-contingent toggling between model-based and random choices (Kikumoto & Mayr, 2019) is confined to competitive situations. Our results provide a very clear answer: The mixed-strategy pattern can be observed even when we carefully avoid any reference to a competitive context. Therefore, we can conclude that the mixed strategy is a general characteristic of choice behavior in uncertain situations.

This work is generally consistent with previous research indicating that people use a mixture of different types of choice strategies in an adaptive manner (Lee, Shimojo, & O'Doherty, 2014). Aside from the model-based and the random choice strategy, our data also show a very strong influence of the memory-free, win-stay/lose-shift bias (Forder & Dyson, 2016, & Hermoso-Mendizabal et. al, 2020). It is noteworthy that this tendency was considerably stronger in the current experiments than in the results by Kikumoto and Mayr (2019) despite the otherwise identical paradigm. Possibly this by itself reflects an adaptive response: In the absence of an obvious opponent who can exploit one's choice regularities this strategy of repeating what was just successful, may appear less risky to participants.

Our results indicate that the mixed model-based/random strategy is a general phenomenon, which opens the floor to some interesting further research considerations. A general tendency for random behavior after losses may have an intersection with learned helplessness in depressed adults. The literature describes learned helplessness as the tendency to stop behaving in a systematic manner when a situation appears uncontrollable (e.g., Maier & Seligman, 2016). It is the possible that the here observed tendency to abandon a mental model after losses is at the heart of this phenomenon. Therefore, it is particularly interesting that this occurs not just in competitive situations, but apparently in a much more general manner. In future work it would be important to test to what degree depressed individuals exhibit an increased tendency towards random behavior following negative feedback

This is just one example of how these findings may be applied to further research. Whether on the soccer field or when navigating day-to-day situations, human cognition is remarkable in the ways that we can apply a finite number of functions to infinite situations and circumstances.

Tables

Trial Outcome	*M*	*SD*
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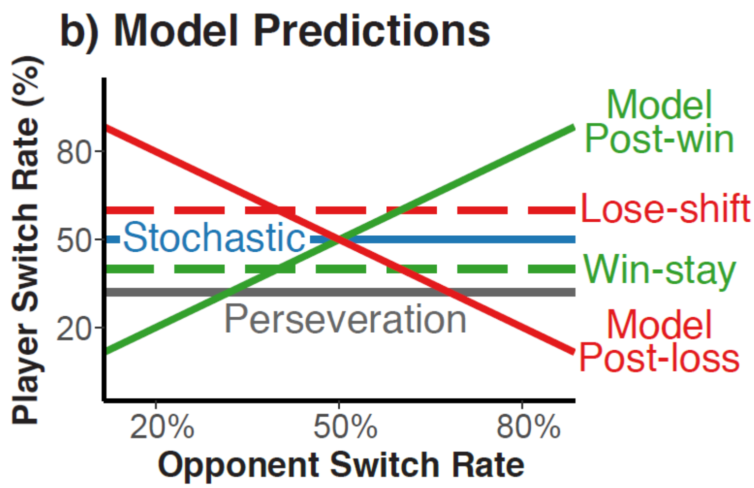
Figures



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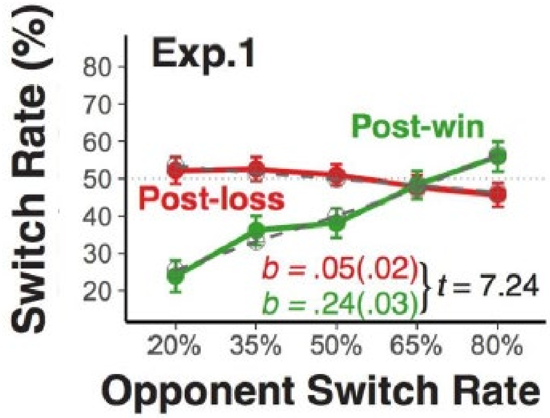

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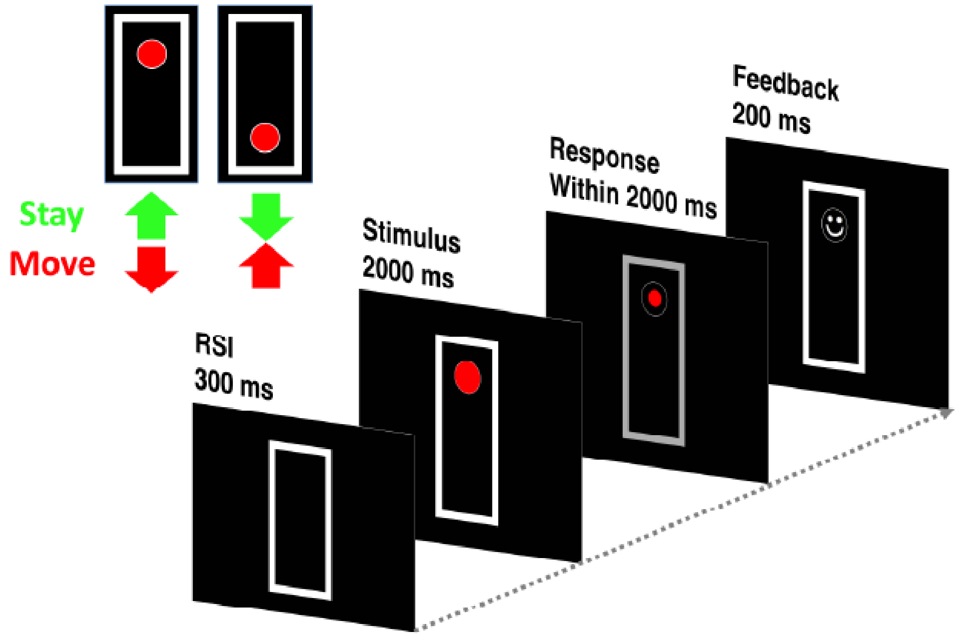

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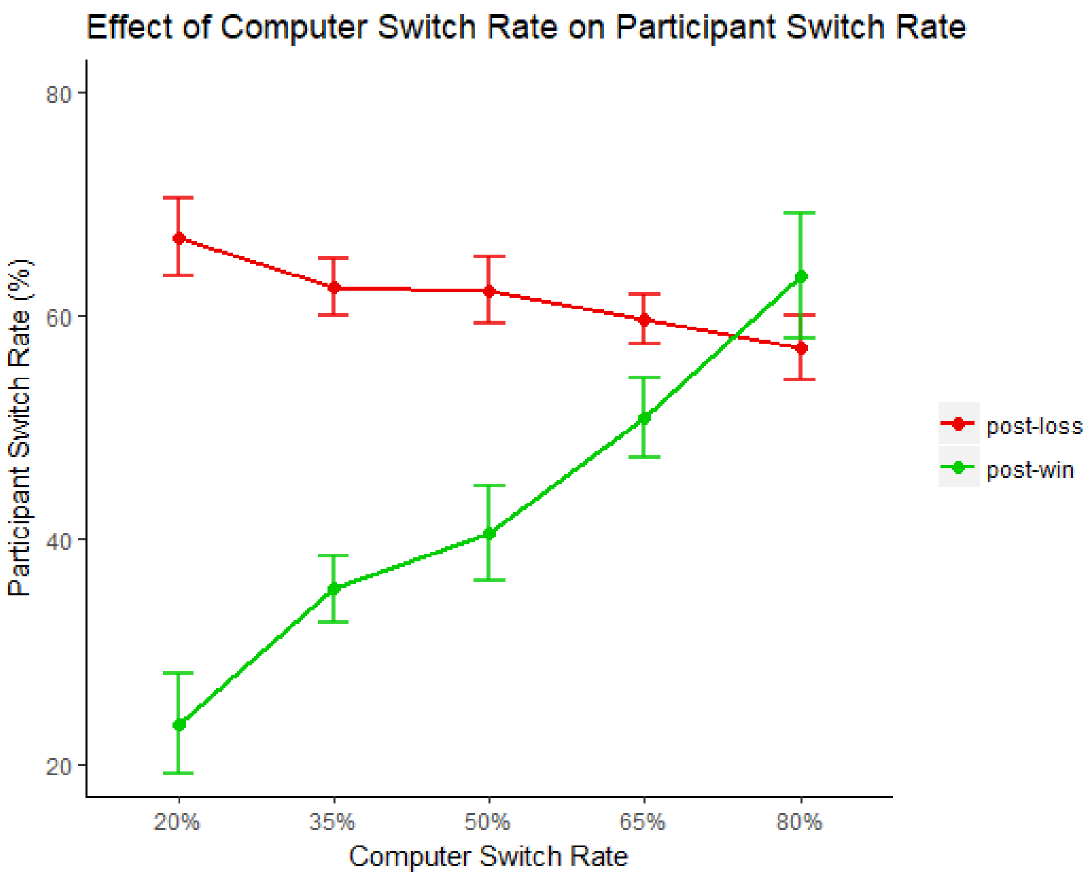

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