Motor effort and adaptive sampling in perceptual decision-making

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Abstract

People usually switch their attention between the options when trying to make a decision. In our experiments, we bound motor effort to such switching behavior during a two-alternative perceptual decision-making task and recorded the sampling patterns by computer mouse cursor tracking. We found that the time and motor cost to make the decision positively correlated to the number of switches and increased with the difficulty of the task. Specifically, the first and last sampled items were decided in an attempt to minimize the overall motor effort during the task, and both were manipulatable by biasing the relevant motor cost. Moreover, the last sampled item was more likely to be chosen, and the cumulative sampling amount also biased to the chosen item during the later phase of the sampling. Assuming that attention switching is independent of the decision variable, conventional attentional drift-diffusion model (aDDM) was inadequate to explain the size of the last-sampling bias in our experimental conditions. Meanwhile, our Bayesian Network analysis showed that the causal relationship between attention and decision is bidirectional. We concluded that the sampling behavior during perceptual decision-making is actively adapted to the motor effort in the specific task settings, as well as the temporary decision.

Introduction

When people try to make a decision between two similar products in a shopping center, they often approach each shelf on which the products are displayed, or even pick them up to have a closer look. If the choice is really difficult to make, people may walk back-and-forth the two shelves for a long time. Many people will start by examining the product around the entrance of the shop, but eventually choose the one near the checkout counter to save some effort. This daily example indicates that our decisions are not solely shaped by the objective values of the alternatives, but also other factors including the motor effort related to the sampling and action execution processes. However, sensorimotor aspects have not been integrated into decision-making studies until recently. It is still an on-going controversy whether action is part of decision-making: According to the Embodied Choice model, action execution is part of the decision-making process rather than merely a means to report the decision; in other words, action can feed back into the decision-making [1]. Under such guidance, studies have been trying to examine decision-making through analyzing movement patterns [2] as well as to seek neural imaging evidence on the involvement of sensorimotor system during decision-making [3]. On the other hand, Aczel et al. [4] argued that the observed bias in decisions was caused by the difference in motor effort needed during action, not by the movement toward one of the options as the Embodied Choice model proposed. There have been several studies focusing on the influence of motor effort during action upon decision-making: Perceptual decision-making has been reported to be biased to the choice associated with less motor cost to respond [5], and such bias still exists in subsequent decisions when no motor effort difference is present [6]. De Lange and Fritsche [7] suggested that motor cost can influence decision-making in a similar manner to rewards. In addition, motor effort can also affect changes of mind during decision-making [8]. However, no investigation has been focused on the motor effort related to the sampling behavior: Although in some studies two or more spatially separated visual stimuli were used as choices during the task, the main form of movement involved during sampling was the eye movement (saccade), of which time cost instead of energy cost seems to be the major consideration [9].

Another issue following the separation of the alternatives in space is the attention allocation during sampling. Typically, the decision-maker switches his attention (behaviorally shown as switching the gaze) between the options at least once, and sometimes multiple times.

What is the relationship between attention and decision-making? Shimojo et al. [10] proposed that the bias in gazing behavior during sampling can both reflect and influence preference decision: such gaze bias to the finally chosen item is continually reinforced, which was named the gaze cascade effect. Other results that manipulations in attention biased choices have been reported as well [11-15], but there is rare evidence supporting that temporary choices can influence attention allocation. Under the assumption that attention can influence value integration during decision-making, the attentional drift-diffusion model (aDDM) was proposed [16]. Unlike the traditional drift-diffusion model, in which the relative evidence accumulates at a constant rate (the drift rate) within one decision, the aDDM allows the drift rate to change with attention: the option currently being attended (gazed at) shall receive more evidence. Such model has successfully explained the gaze patterns and several gaze-related biases in preference-based and perceptual decisions performed by human subjects [16, 17, 18]. Specifically, the aDDM assumes that the attention or gaze switches between the options randomly. Previously reported gaze cascade effect that preference affects attention can be readily explained by aDDM. Therefore, Krajbich [19] suggested that gaze or attention have a causal effect on choice, but not vice versa.

Under natural circumstances, humans actively gather information with attention and active sensing behaviors (shift of gaze and assisting limb/body movement) to sample relevant cues [20]. Sampling behavior itself can be regarded as a low-level decision-making process about what information to acquire, as well as where and when [21]. In this study, we aim to figure out the factors influencing sampling patterns during a basic perceptual decision-making task, especially how sampling behavior is adapted to the expected motor effort given the specific environment where the task is performed. We designed a paradigm in which motor effort was bind to the sampling and action execution processes, and manipulated the expected motor cost to examine corresponding changes in the sampling patterns. Additionally, we tested the causal relationship between the temporary decision and the attention allocation strategy during sampling by stimulating an aDDM and analyzing a Bayesian Network model.

Results

The visual stimuli in the task were two groups of black and white dots positioned separately at the left and the right side of the screen, and subjects were asked to decide in which group there were more white dots than in the other. In order to bind motor effort to the sampling process, we applied an artificial rule that 'the sampling quality is in proportion to the distance between the agent and the alternative choice', which in natural circumstances can be interpreted as 'the closer one gets to look at an object, the more details can be seen', and 'getting closer' needs motor effort. During sampling, a number of randomly selected dots were made invisible in each frame, and the number was in proportion to the distance between the cursor and each dot stimulus (Fig 1A). In this way, to get better sampling quality, subjects must make some motor effort to move the cursor closer to the stimulus they want to examine. The start position was randomly set between the two stimuli, and subjects were instructed to drag the cursor onto that position to initiate each trial. The motor effort in the action stage took the form of moving the cursor to the corresponding choice button placed below the dot stimuli on the screen and clicking on it to make the choice. We set two types of tasks: In the first type, the choice buttons were horizontally centered (Fig 1A), so the two stimuli were equally close to them, which made the motor effort required to move the cursor from each stimulus to the buttons approximately the same. In the second type, the choice buttons were positioned below the right stimuli (Fig 1B), so that the right stimulus was closer to them than the left one, thus the required motor effort would be less if the right one was last sampled.

Fig 1. Binding motor effort to the sampling and action execution stages of the decision-making task. (A) The level of invisibility of each stimulus is in proportion to the distance between the current position of the mouse cursor and the two stimuli. The choice buttons are horizontally centered, so the distance from the two stimuli to the buttons are approximately the same. **(B)** The choice buttons are horizontally biased to the right, so the distance from the right stimulus to the buttons is shorter than that from the left.

General Sampling Patterns

We plotted the horizontal mouse cursor position recorded during the sampling period at each time point. Fig 2 shows the typical cursor position time series from a single block for one of the subjects. The 60 trials in the block were sorted by the start position. The length between the two stimuli was linearly mapped to a 0-to-1 scale and shown in a red-blue color gradient. The graph implies that the typical sampling pattern was to switch the cursor once or multiple times between the two stimuli. The cursor paused mostly at either the left-most or right-most part, which means only one of the stimulus was clearly visible at the time. Therefore, we can make the assumption that the eye gaze and the attention of the subject switched between the stimuli together with the cursor, which enables the comparison of our paradigm and former sequential sampling tasks and models.

Fig 2. Horizontal mouse cursor position plotted as time series during the trials. Data is from a single block (60 trials) performed by one subject and sorted by the start position in each trial. Red color indicates the cursor is currently positioned more to the right stimulus, while blue indicates left.

Under this sampling pattern, if a subject made n switches in a trial, there would be n+1 periods of sampling alternatively assigned to the two stimuli. Assuming that each sampling period has approximately the same duration, the total decision time (elapsed time from the beginning of the trial to when the decision is made, excluding the time to execute the action) should be correlated to the number of switches. On the other hand, most of the motor effort during sampling was spend on the switching movement, and a typical switch would be moving the cursor from the left stimulus to the right, the distance between them fixed. Therefore, the total motor effort during the trials, measured by the total horizontal moving distance of the cursor on the screen, should be correlated to the number of switches, too. Based on this, in order to minimize the time and motor cost during sampling, subjects should make as few switches as possible. The actual behavioral results well matched our analysis: Fig 3A plots the number of switches made in all trials across the subjects in a histogram. In 42.5% trials only one switch was made, and the percentage of trials got lower when more numbers of switches were made. Moreover, the proportion of trials with higher distinctions between the two stimuli was larger among the trials with fewer switches than among those with more switches. Fig 3B and 3C show that the decision time and the total horizontal moving distance of the cursor correlated to the number of switches significantly (Spearman's ρ = 0.71, $P = 2.0\times10^{-148}$ for decision time and ρ = 0.84, $P = 3.7\times10^{-261}$ for horizontal moving distance). The results are in accordance with the speed-energy-accuracy trade-off rule: in order to maintain high accuracy in the perceptual decision-making task, subjects would invest more time and motor cost when the task was more difficult.

Fig 3. Number of switches between the stimuli, and its correlation to decision time and the total horizontal moving distance of the cursor on the screen during the trials. (A) Histogram of the number of switches in all trials, colors indicating the absolute distinction between the two choices. **(B)** Correlation of decision time and number of switches during the trials. Spearman's $\rho = 0.71$, $P = 2.0\times10^{-148}$. **(C)** Correlation of total horizontal moving distance of the cursor and number of switches during the trials. Spearman's $\rho = 0.84$, $P = 3.7\times10^{-261}$. Error bars show 95% confidence intervals for data pooled across all subjects.

Influences of Motor Cost on Sampling Patterns

Apart from the general influence of task difficulty on the number of switches during sampling, the difference in motor cost depending on the start position and the choice button position can also affect sampling patterns. In the centered choice button condition and the right biased choice button condition, the psychometric choice curves (Fig 4A) were not significantly different, and the overall accuracy was also very similar (90.4% for centered choice button task and 91.5% for right biased choice button task). As the absolute distinction between the two choices increased, the number of switches (Fig 4B, Spearman's $\rho = -0.41$, $P = 2.6\times10^{-40}$ for centered condition and $\rho = -0.37$, $P = 4.0\times10^{-33}$ for right biased condition), decision time (Fig 4C, Spearman's $\rho = -0.28$, $P = 7.4\times10^{-19}$ for centered condition and $\rho = -0.46$, $P < 10^{-300}$ for right biased condition) and horizontal moving distance (Fig 4D, Spearman's $\rho = -0.35$, $P = 1.7\times10^{-28}$ for centered condition and $\rho = -0.35$, $P = 2.3\times10^{-29}$ for right biased condition) in the trials all decreased, but there were no significant difference between the centered and right biased conditions. Fig 4E shows the psychometric curves for the first sampled stimulus. The subjects tended to sample the stimulus closer to the start position in the trial, but with a systematic bias (usually to the left stimulus). This bias may be related to the cultural habit of dealing with items from left to right, for example while reading people usually start from the left. In the centered choice button condition, moving firstly to the stimulus closer to the start position would minimize the total horizontal moving distance during sampling. However, when the choice buttons were biased to the right stimulus, if the subject expected to make only one switch (which was most likely, see Fig 3A), the sampling strategy to minimize motor cost would be to go for the left stimulus first and then the right, finally taking the shorter path from the right stimulus to the choice buttons. Such additional bias to sample the left stimulus first when the choice buttons were biased to the right was indeed observed in subjects' behavior (Fig 4E). Regardless of the previous sampling sequence, it would always take less motor effort to execute the action if the subject sampled the right stimulus lastly in the right biased choice button condition. Fig 4F shows that subjects were more likely to sample the right stimulus last in the right biased choice button condition compared to the centered condition. Such a tendency was more significant for the trials in which the distinctions between the choices were low. In summary, the attempt to minimize motor cost during sampling as well as action execution can influence which stimulus to sample firstly and lastly.

Fig 4. Psychometrics for centered choice button task versus right biased choice button task. (A) Psychometric choice curves. **(B)** Number of switches between the stimuli. Spearman's $\rho = -0.41$, $P = 2.6\times10^{-40}$ for centered condition and $\rho = -0.37$, $P = 4.0\times10^{-33}$ for right biased condition. **(C)** Decision time. Spearman's $\rho = -0.28$, $P = 7.4\times10^{-19}$ for centered condition and $\rho = -0.46$, $P < 10^{-300}$ for right biased condition. **(D)** Total horizontal moving distance of the cursor. Spearman's $\rho = -0.35$, $P = 1.7\times10^{-28}$ for centered condition and $\rho = -0.35$, $P = 2.3\times10^{-29}$ for right biased condition. **(E)** First sampled psychometric curves. **(F)** Last sampled choice bias. Significance levels are based on unpaired one-tail t-test, $*P < 0.05$, $***P < 0.001$. Error bars show 95% confidence intervals for data pooled across all subjects. Shaded error bars show 95% confidence intervals based on generalized linear model fitting.

Choice Biases Related to Sampling Processes

Firstly, the aDDM predicts a last-sampling bias, which means that subjects are more likely to choose the last sampled stimulus. That is because the discounted rate of evidence accumulation for the stimulus not being sampled will lead to the result that the decision variable is more likely to reach the barrier at the last sampled side [16]. Such bias has been reported in a number of human decision-making studies of both value-based and perceptual decisions [16, 18]. However, the causal relationship behind the last-sampling bias is not completely clear: While the aDDM assumes that the current decision variable has no backward influence upon sampling patterns, there is rare evidence supporting or contradicting the causal effect of the temporary decision on the attention allocation during sampling [19].

In order to test whether the subjects tended to choose the particular stimulus because they sampled it lastly, or the subjects tended to sample the particular stimulus lastly because they wanted to choose it, or both, we set up a new type of sampling mode: The subjects should and could only make one switch between the stimuli, which means they had only one chance to sample each of the alternatives. The time to examine each stimulus was not limited, though. In this condition, the last sampled item would have been already decided when the subject started to sample the first stimulus, therefore it cannot be affected by the decision variable later. We built an aDDM and fitted its parameters to the behavioral data in the unlimited-switch mode, then we compared the size of the last-sampling bias in the unlimited- and one-switch sampling mode for human behavior and model output.

As Fig 5 shows, the aDDM fitted the basic psychometrics including the choice curve (Fig 5A), decision time (Fig 5B) and the number of switches (Fig 5C) in the unlimited-switch mode generally well. In the one-switch mode (Fig 5D and 5E), the decision time of the model output was similar to that of the human behaviors, but note that the overall accuracy (79.9%)

was lower compared to behavioral data (89.1%). In fact, the human subjects' overall accuracy in the one-switch condition was not reduced obviously compared to that in the unlimited-switch condition (90.4%). This result is quite surprising, for in the one-switch mode the decision time was shorter, and this normally should lead to lower accuracy. If the accuracy has not been significantly improved by making further switches, which would cost extra time and energy, why would the subject make them? One possible reason is that subjects would like to check the previously sampled stimuli again to verify their preliminary decision [22], which would increase the confidence in their decision.

Fig 5. Psychometrics for human subjects' behavioral data versus fitted aDDM output. (A) Psychometric choice curves in the unlimited-switch task. **(B)** Decision time in the unlimited-switch task. **(C)** Number of switches in the unlimited-switch task. **(D)** Psychometric choice curves in the one-switch task. **(E)** Decision time in the one-switch task. Error bars show 95% confidence intervals for data pooled across all subjects. Shaded error bars show 95% confidence intervals based on generalized linear model fitting.

We then compared the last-sampling bias in our model output and that in the subjects' behavioral data: In the unlimited- and one-switch mode, both human behavior and model output exhibited a bias to choose the last sampled stimulus (Fig 6). However, in the unlimited-switch mode, the bias size for model output was smaller than human behavior: When the distinction between the two choices was zero, the difference in the fitted probability of choosing right when right was last sampled versus when left was last sampled (Δp) was 0.59 for human subjects but only 0.27 for the model (Fig 6A). Such deducted size of the last-sampling bias in fitted aDDM compared to human data has also been reported in another perceptual decision-making study, where Δp = 0.51 for human data and Δp = 0.26 for aDDM [18]. Moreover, compared to the unlimited-switch mode, the size of the last-sampling bias decreased for human behavior (Δp = 0.30) but increased for model output (Δp = 0.47) when only one switch was allowed (Fig 6B).

Fig 6. Last-sampling bias for human subjects' behavioral data versus fitted aDDM model output. **(A)** Last-sampling bias in the unlimited-switch mode. **(B)** Last-sampling bias in the one-switch mode. Shaded error bars show 95% confidence intervals based on generalized linear model fitting.

To quantify the size of the last-sampling bias, we built a Bayesian Network model depicting the causal relationship between the last sampled item and the decision.

$$\begin{aligned} & p\left(\text{right last chosen}\middle|\text{right last sampled}\right) \\ & = \int p\left(\text{right chosen}\middle|\boldsymbol{DV},\text{right last sampled}\right) p\left(\boldsymbol{DV}\middle|\text{right last sampled}\right) d\boldsymbol{DV} \\ & = \int p\left(\text{right chosen}\middle|\boldsymbol{DV},\text{right last sampled}\right) \frac{p\left(\text{right last sampled}\middle|\boldsymbol{DV}\right)}{p\left(\text{right last sampled}\right)} p\left(\boldsymbol{DV}\right) d\boldsymbol{DV} \end{aligned} \qquad (2)$$

Equation (1) gives the general form of conditional dependence relationship behind the last-sampling bias: p(right chosen | right last sampled) is the probability of choosing the right item given that the right item is last sampled. $\boldsymbol{DV}$ is the decision variable at the time the last sampling starts, and $p(\boldsymbol{DV})$ is its prior distribution. When the distinction between the two choices is 0, the expected $\boldsymbol{DV}$ is also 0. If the subjects have a tendency to choose the last sampled item, p(right chosen | $\boldsymbol{DV}$, right last sampled) should be higher. On the other hand, if the subjects have a tendency to sampled the item that the current decision variable biases to, the likelihood p(right last sampled | $\boldsymbol{DV}$) should be higher when $\boldsymbol{DV}$ is closer to the right barrier and lower when $\boldsymbol{DV}$ is closer to the left barrier. p(right last sampled) can be regarded as a constant value irrelevant to $\boldsymbol{DV}$.

Altogether, there are three possible hypotheses regarding the causal relationship between the last sampled item and the decision: Fig 7A displays the graphical models for these hypotheses. Model (a) as well as the aDDM assumes that the final decision is dependent on the last sampled item, but the last sampled item is independent of the decision variable. In the aDDM, for each given $\boldsymbol{DV}$, p(right chosen | $\boldsymbol{DV}$, right last sampled) is decided by the value scaling parameter d, the noise level parameter σ and the discounting parameter θ for the unattended item, and the mean is higher than 0.5. Since the last sampled item is independent of $\boldsymbol{DV}$, we have:

$$p\left(\text{right chosen}\middle|\text{right last sampled}\right) = \int p\left(\text{right chosen}\middle|\boldsymbol{DV},\text{right last sampled}\right)p\left(\boldsymbol{DV}\right)d\boldsymbol{DV} \tag{3}$$

Therefore, the bias is solely due to the term p(right chosen | $\boldsymbol{DV}$, right last sampled). In the one-switch mode, the elapsed time before the last sampling is shorter, thus $p(\boldsymbol{DV})$ will have smaller variance so that p(right chosen | right last sampled) will become even larger, which is in accordance with the actual model stimulation results (Fig 6B). Similarly, the value of p(right chosen | right last sampled) should be the same for centered and biased choice buttons. However, if we assume that the last sampled item is dependent on $\boldsymbol{DV}$ but the final decision is independent of the last sampled item, as in Model (b), we shall have:

$$p\left(\text{right last chosen}\middle|\text{right last sampled}\right) = \int p\left(\text{right chosen}\middle|\boldsymbol{DV}\right)\frac{p\left(\text{right last sampled}\middle|\boldsymbol{DV}\right)}{p\left(\text{right last sampled}\right)}p\left(\boldsymbol{DV}\right)d\boldsymbol{DV} \tag{4}$$

In this model, the bias is due to the term p(right last sampled | $\boldsymbol{DV}$) instead, while the term p(right chosen | $\boldsymbol{DV}$) is unbiased. If only one switch is allowed, the last sampled item can no longer depend on $\boldsymbol{DV}$, so we have:

$$p\left(\text{right last chosen}\middle|\text{right last sampled}\right) = \int p\left(\text{right chosen}\middle|\boldsymbol{DV}\right)p\left(\boldsymbol{DV}\right)d\boldsymbol{DV} \tag{5}$$

And the mean of p(right chosen | right last sampled) will fall back to 0.5. In the biased choice button task, the last sampled item depends on not only $\boldsymbol{DV}$ but also motor cost considerations, so the slope of likelihood p(right last sampled | $\boldsymbol{DV}$) will become smaller compared to the centered choice button condition, resulting in the reduced bias size in p(right chosen | right last sampled). Finally, model (c) shows a third possibility that the last sampled item is dependent on $\boldsymbol{DV}$, and the final decision is also dependent on the last sampled item. In this model the mathematical expression takes the full form in Equation (1), and the total bias in p(right chosen | right last sampled) has two sources: The last sampled item is more likely to be chosen, so p(right chosen | $\boldsymbol{DV}$, right last sampled) is biased; the currently winning item is more likely to be last sampled, so p(right last sampled | $\boldsymbol{DV}$) is also biased. Under such an assumption, in the one-switch mode the last-sampling bias should still exist because the term p(right chosen | $\boldsymbol{DV}$, right last sampled) is biased, but the size will decrease because the term p(right last sampled | $\boldsymbol{DV}$) now disappears. In the biased choice button task, the bias will also become smaller because the last sampled item is now dependent on an extra factor related to the motor cost. Fig 7B shows p(right chosen | right last sampled) for human subjects' behavioral data in the three experimental conditions: Compared to the centered unlimited-switch condition, in the one-switch mode p(right chosen | right last sampled) decreased but was still higher than 0.5 when the distinction between choices was zero, while in the right biased button task the size of the last-sampling bias also decreased. Among the three hypotheses, only Model (c) correctly predicted the behavior of the subjects. Therefore, we drew the conclusion that the causal relationship between sampling patterns and the decision is bidirectional.

Fig 7. Causal relationship for the last-sampling bias. (A) Graphical models for possible hypotheses of the conditional dependence relationship between the last sampled stimulus and the decision. Arrows show dependency between the events or variables, and dashed arrows show dependency assumed to exist in the model, but made impossible under certain experimental conditions. **(B)** Probability of choosing the right item given the right item is last sampled for human subjects' behavioral data. The last-sampling bias exists in all three conditions, but the size is smaller in one-switch and right-biased choice button tasks. Shaded error bars show 95% confidence intervals based on generalized linear model fitting.

In addition, the aDDM also predicts that the subjects are more likely to choose the stimulus with longer overall sampling time. In our paradigm, the noise level for the stimuli is varying during the trial, therefore we changed the sampling time length to the cumulative sampling amount (CSA), which is defined as the integral of the proportion of visible dots with respect to time for each stimulus. Instead of focusing merely on the overall sampling amount, we studied the time course of the correlation between the CSA and the final choice: We plotted the odds ratio ($N_{\text{left CSA larger, left chosen}} \cdot N_{\text{right CSA larger, right chosen}} \cdot N^{-1}_{\text{left CSA larger, right chosen}} \cdot N^{-1}_{\text{right CSA larger, left chosen}}$, in which N is the number of trials across all subjects) for the three experimental conditions as time series in Fig 8. Note that the average finishing time of the first sampling is at 1345 ms, and the second sampling at 2256 ms. There are a few interesting phenomena shown in the results: First, only in the unlimited-switch mode with centered choice buttons the overall CSA was significantly correlated to the final choice. Second, such correlation became significant only in the later period of the sampling process. Third, in the one-switch mode, subjects tended to sample the stimulus with fewer white dots (the wrong choice) first and save the stimulus with more white dots (the correct choice) for the second, which is also the last sampling. As a result, there was a significant negative correlation between the first sampled stimulus and the final choice in the one-switch mode, which was not found in the other two conditions. Recall that the further switches made in the sampling process have not improved the accuracy of the decision much. Combined with the fact that the extra sampling was mostly spent on the finally chosen stimulus (but the decision has already formed after the first two samplings), we deduce that sampling patterns in the later period depend on the preliminary decision: Subjects will make extra switches to and spend extra time dwelling on the predetermined choice in order to verify their decision. Moreover, when the subjects know in advance that only one switch can be made, even the earlier period of the sampling process can be influenced by the decision variable. However, other factors, for example motor cost considerations can disrupt such verifying sampling behavior.

Fig 8. Correlation of the cumulative sampling amount and the final choice plotted as functions of the elapsed time in the trials. (A) Odds ratio of choosing the stimulus with higher cumulative sampling amount till the specific time point in the trials versus not choosing it. **(B)** The first 2000 ms enlarged. **(C)** Proportion of trials already ended before the specific time point.

Discussion

In summary, the adaptive sampling behavior during perceptual decision-making exhibits the following patterns: First, the number of switches between the alternatives as well as the total time and motor cost during sampling is related to the difficulty of the task: the more difficult the task is, the more times the stimuli are resampled. Second, the sampling order depends on the start position and the choice button position in an attempt to minimize the total moving distance of the mouse cursor. Third, attention biases to the eventually chosen item during the later phase of the sampling. Combining the modeling results, we conclude that the sampling pattern is shaped by both motor cost and the current decision. We integrate our findings into the previous framework and draw a new model for decision-making process considering motor effort during sampling and action (Fig 9): (b) *The current decision variable* *influences sampling patterns* and (e) *motor cost influences sampling patterns* together depict the adaptive nature of sampling during decision-making.

Fig 9. Model for decision-making process considering the motor effort in both sampling and action. (a) Sampling patterns influence the decision. **(b)** The current decision variable influences sampling patterns. **(c)** The final decision is translated into action. **(d)** Action properties influence the decision. **(e)** Motor cost influences sampling patterns. **(f)** Motor cost influences action.

Wispinski et al. [23] reviewed recent computational models, behavioral studies and neural recordings, and drew the conclusion that decision-making is a continuous process from the presentation of behaviorally relevant options until movement completion. Previous studies suggested that motor effort related to the action phase can influence the decision [4-6, 8], and our results expand the conclusion to that the sampling behavior can also be influenced by motor effort related to both sampling and action. It further supports the idea that sensorimotor aspects should be considered as an actively integrated part of the decision-making process. However, while our manipulation of motor effort biased the last sampled item, it did not bias the choices made by the subjects. One possible reason is that the choice is not relevant to the motor effort difference in the task; another possibility is that explicit knowledge of the motor cost will help to avoid integrating irrelevant factors into the decision to maintain high accuracy [24]. In addition, there are several studies focusing on the representation of motor effort and how it is related to cost minimization in decision-making as well as motor control [25, 26]. Future studies may further quantify the effect of motor cost on decision-making based on similar methods.

The relationship between attention and eye movement during decision-making has been studied abundantly [27], but researches that highlight limb and body movements during the sampling process are rare, even though in naturalistic circumstances such movements usually accompany and cooperate with eye movements in order to get best sampling of information. In our research, we designed a paradigm based on computer mouse tracking in which both gaze shift and hand movement (moving the mouse) are necessary to switch attention between the options. Although mouse tracking and eye tracking are both commonly applied process tracking methods in decision-making research, their original purposes are slightly different: While eye tracking mostly target on attention and information searching strategies, mouse cursor tracking data reflect more about indecision and momentary preference [28]. In our paradigm however, subjects must move the cursor closer to get a better view of each stimulus, as if approaching a real object to have a better look. In this way, the mouse trajectory can reflect attention during sampling as eye traces did in previous studies. Moreover, our paradigm can be applied to study eye-hand cooperation and coordination during decision-making as well.

Traditionally, sequential sampling models assume that during decision-making, subjects sample their options continuously until the relative evidence for one option reaches a predetermined threshold, and such models capture the speed-accuracy trade-off phenomenon well [19, 29, 30]. In our study, the decision time correlated to the difficulty of the decision, which is in accordance with previous theories. However, our results showed that subjects would make extra switches between the items and spend more time during which the accuracy of the decision has not been improved significantly. Specifically, these extra switches were biased to the choice eventually made. According to Krajbich [19], even as the decision variable evolves and one option emerges as the winning one, it is still optimal to continue sampling information randomly instead of favoring the leading option, since the information from both the winning and losing options are of equal importance. In contrast, other studies [10, 31, 32] as well as our results reported a clear bias to examine the finally chosen option more during the later phase of sampling. Mullett and Stewart [31] suggested that such bias may be due to a relative instead of absolute stopping rule. In fact, allowing the current decision variable to feed back into the sampling patterns will push the decision variable further to the leading option and accelerate the decision process. Such acceleration will not necessarily reduce the accuracy of the decision, because it only happens at the later stage of sampling in which the main task is just to validate the decision. This validating phase may be longer for perceptual decisions, for people tend to respond with more caution in perceptual decisions than in preferential decisions, especially when the stimuli are ambiguous [33]. Meanwhile, how these sub-thresholds within the preliminary decision phase and the validating phase are determined remains to be discussed.

Finally, our study provided evidence for the bidirectional causal relationship between attention during sampling and decisions by a Bayesian Network analysis. Bayesian Networks have been customarily applied for probabilistic causal dependence assessment and inference in a wide range of areas [34], including life science researches [35, 36]. It is capable of depicting and predicting the conditional dependences between experimental variables through observed data, thus becomes a very helpful tool for psychological studies. In our practice, we listed all possible network structures, which correspond to different hypotheses on the causal relationship between the last sampled item, the decision variable and the chosen item, and compared the predicted conditional probability of choosing the last sampled item with behavioral data. Contradicting previous literature [19], our results imply that attention is not randomly switching between the options but drawn to the winning item during the later stage of the sampling. This may lead to some modification to the basic assumptions of the aDDM in the future.

Methods

Participants

A total of 24 subjects participated in the study (13 females, age 20 – 30); all of them were university students. Subjects wore glasses for eyesight correction if needed. In order to avoid interference of previous experimental modes upon later sampling patterns, we divided the subjects into 3 groups, each containing 8 subjects, and asked each group to perform under only one mode (Centered: 4 females, mean age 25.9; Right Biased: 5 females, mean age 26.1; One-Switch: 4 females, mean age 24.9). The research was approved by the institutional ethics committee of Eotvos Lorand University, Hungary. All subjects provided informed written consent, and none declared any history of neurological diseases.

Paradigm and Stimuli

The paradigm was based on a two-alternative perceptual decision-making task: There were two imaginary circles on the left and right side of the screen (diameter 3.5 cm, distance 20 cm between the centers), each containing 100 dots. The dots were either black or white on a 50% gray background, and the proportions of white dots were different between the two groups. Subjects must decide in which group there were more white dots than in the other. To trigger each trial, subjects should use the computer mouse to drag the cursor to a small square box located at a random position (uniformly drawn from the central 80% range between the boundaries of the two stimuli), and stay there for a short period of time (1000 – 1500 ms randomly). After the trial was triggered, the two dot stimuli and two choice buttons would appear on the screen (Fig 1).

In the paradigm, a number of randomly selected dots were set invisible in each frame, and the number was in proportion to the distance between the cursor and each dot stimulus (Fig 1A). Subjects were told to avoid pausing the mouse cursor in the middle of the screen while looking at the stimuli on the two sides. In the unlimited-switch sampling mode, subjects could check each stimulus for as many times as they thought necessary. In the one-switch sampling mode, each stimulus could be examined only one time: after the cursor approached close enough to the stimulus (minimum 90% visibility) and then left, this stimulus would be masked and could not be examined again in this trial. Subjects were instructed not to move their mouse to masked stimuli during the task. System mouse acceleration was canceled to ensure the cursor movement on the screen was approximately linearly mapped to the actual movement of the mouse. Subjects were told not to pick up the mouse from the surface of the desk amid each trial.

We asked the subjects to move the cursor to the button corresponding to their choice (left stimulus – left button, and vice versa) and click on it to complete the trial. The choice buttons were positioned below the dot stimuli (vertically 7 cm from the centers of the stimuli) so that the y-axis downward movement of the mouse cursor would mark the start of the action execution stage. We set two types of tasks: In the first type, the choice buttons were horizontally centered (Fig 1A); in the second type, the choice buttons were positioned below the right stimuli (Fig 1B). The distinction between the two choices was defined as the difference between the proportions of white dots in the two groups. In each trial, we randomly drew an average proportion A from 40% – 60%, and then drew separately a distinction proportion D from 0% – 30%, so the proportion of white dots for the two groups would be $A \pm 0.5D$. We randomly assigned the two calculated proportions to the left and right group, making sure that in half of the total number of trials there were more white dots in the left.

The display screen had a width of 28.5 cm and a height of 18 cm, resolution 1280×800 pixels, refresh rate 60 Hz. The screen was placed at a normal distance in front of the subjects when using computers (approximately 50 – 70 cm). We recorded the mouse trajectory from the moment the trial was triggered to when a button was clicked and the final decision in each trial for later analysis. The stimuli and mouse tracking codes were programmed in MATLAB Psychtoolbox-3.

Modeling

We built an aDDM following the framework proposed by Krajbich et al. [16]. The relative value for each dot stimulus was set as:

$$\begin{cases} r_{\text{left}} = kp_{\text{left}} \\ r_{\text{right}} = kp_{\text{right}} \end{cases} \tag{6}$$

Here p_{left} and p_{right} were the proportion of white dots in each stimulus. The range of p_{left} and p_{right} in the experiment was 0.25 – 0.75; we set constant $k = 4$ so the range of r_{left} and r_{right} was 1 – 3. The decision variable (DV) started from 0 in each stimulation, and the decision barriers were +1 for choosing the left stimulus and –1 for choosing the left stimulus. We used the multiplicative model [37]: the drift rates (v) in the model were given as:

$$\begin{cases} v = d\left(r_{\text{left}} - \theta r_{\text{right}}\right), \text{left attended} \\ v = d\left(\theta r_{\text{left}} - r_{\text{right}}\right), \text{right attended} \end{cases} \tag{7}$$

Here d was the value scaling parameter, and θ was the multiplicative attentional discounting parameter. Let DV_t denote the value of the decision variable at time t. For every time step Δt, we have:

$$DV_{t+\Delta t} = DV_t + v\Delta t + \varepsilon_t \tag{8}$$

ε_t was drawn from zero mean Gaussian distribution with standard deviation σ. We assume that the first sampling is to the left stimulus with a fixed probability, and its duration drawn from a fixed distribution. Each following sampling is made alternatively between left and right which will continue until it reaches a max time limit drawn from a fixed distribution or the decision variable reaches one barrier. We then fitted the three parameters in the model (θ, d and σ) to the overall accuracy and the number of switches made in each trial for human behavioral data. The best fitting set of parameters was $\theta = 0.52$, $d = 0.0097$ and $\sigma = 0.018$. The fitted decision time (T) was calculated in the following way:

$$T = kt + nt_0 \tag{9}$$

Here t denoted the decision time in the stimulation, k the time scaling factor, n the number of switches in the stimulation, and t_0 the fixed time spent on switching between the stimuli. k and t_0 were fitted to the behavioral data.

For the one-switch mode, there are two possible models regarding the stop rule for the second and last sampling: the second sampling can stop either when the decision variable reaches one barrier or when its duration reaches the limit, or it can go on until one barrier is reached without max time limit. The latter version fitted the decision time for human subjects in the one-switch mode better, therefore we applied this assumption.

After the parameters for the aDDM were fitted, we ran the stimulation for 960 trials (sample size equal to 120 trials multiplied by 8 subjects) in both the unlimited- and one-switch sampling modes, and compared the output with human behavioral data.

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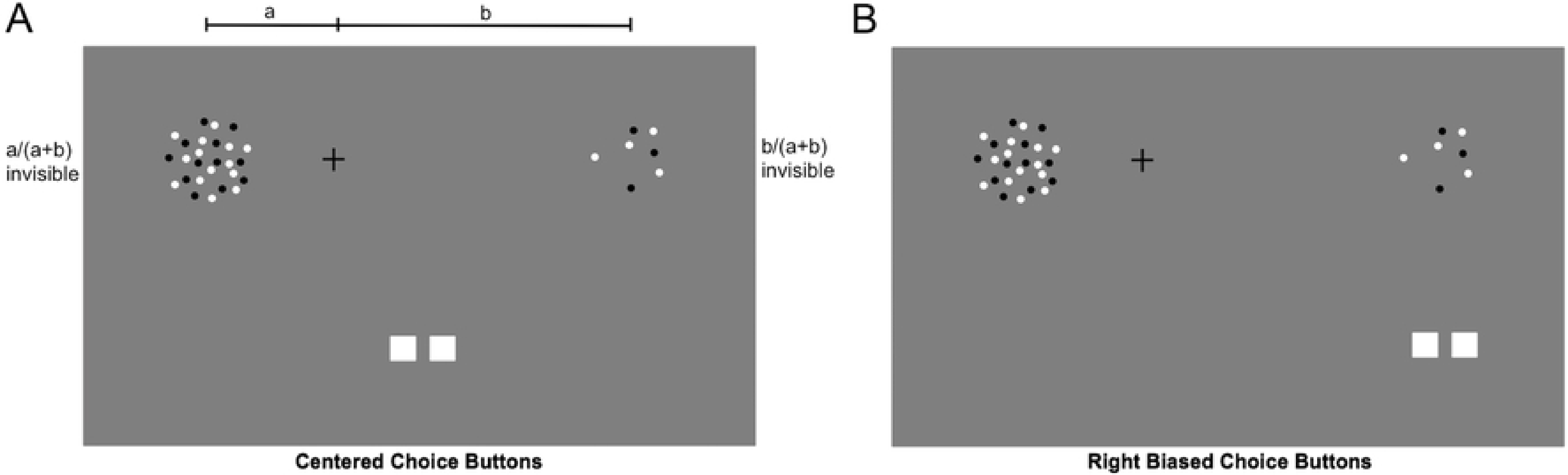
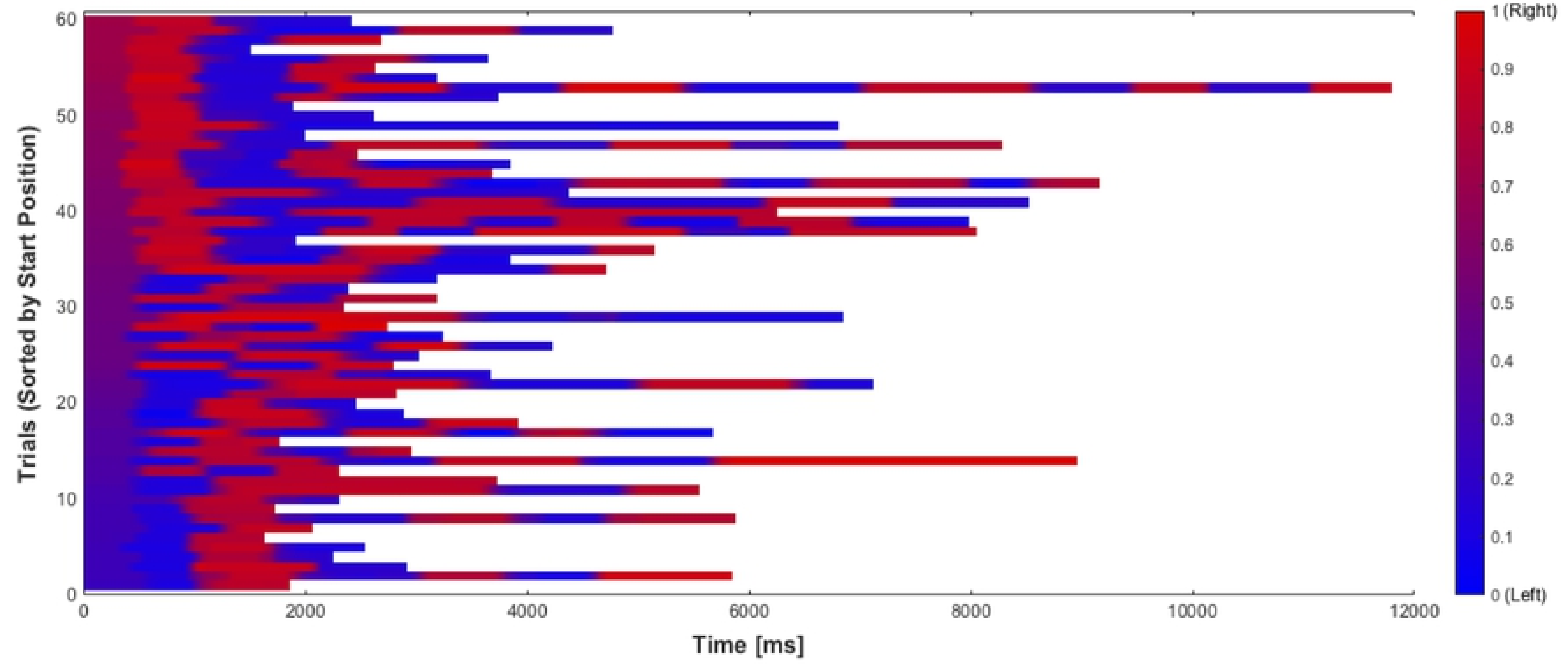
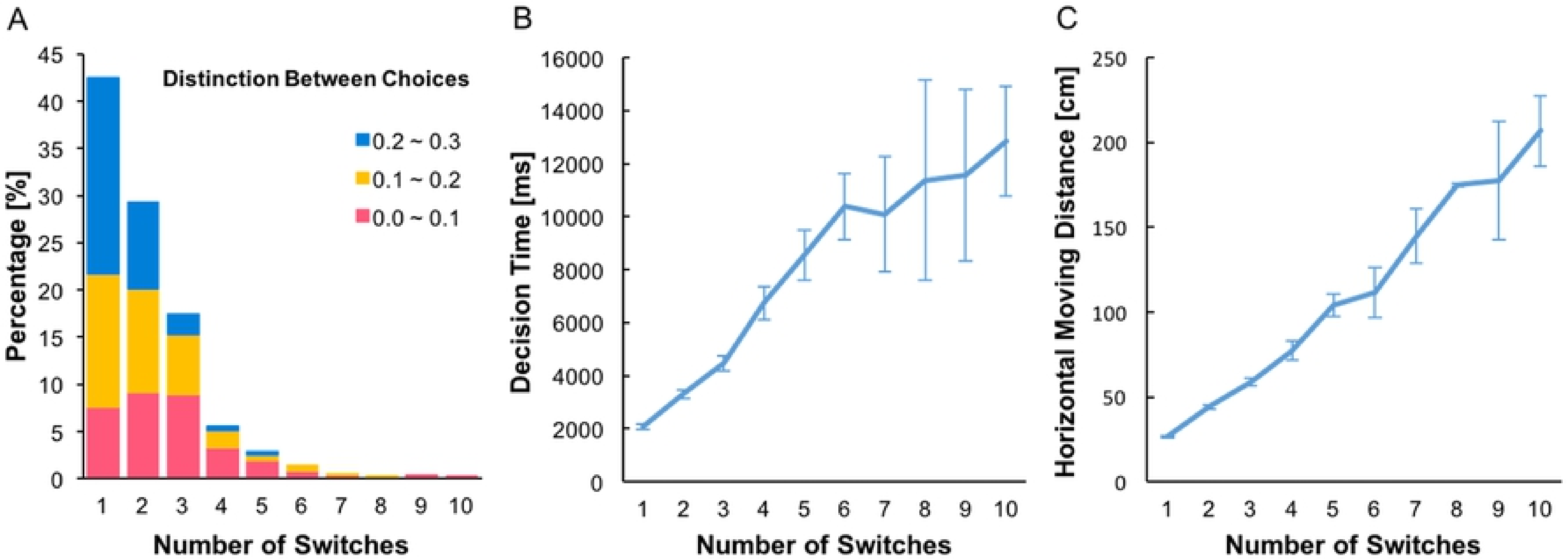

A
a
b
a/(a+b)
invisible
b/(a+b)
invisible
Centered Choice Buttons
B
Right Biased Choice Buttons

Figure

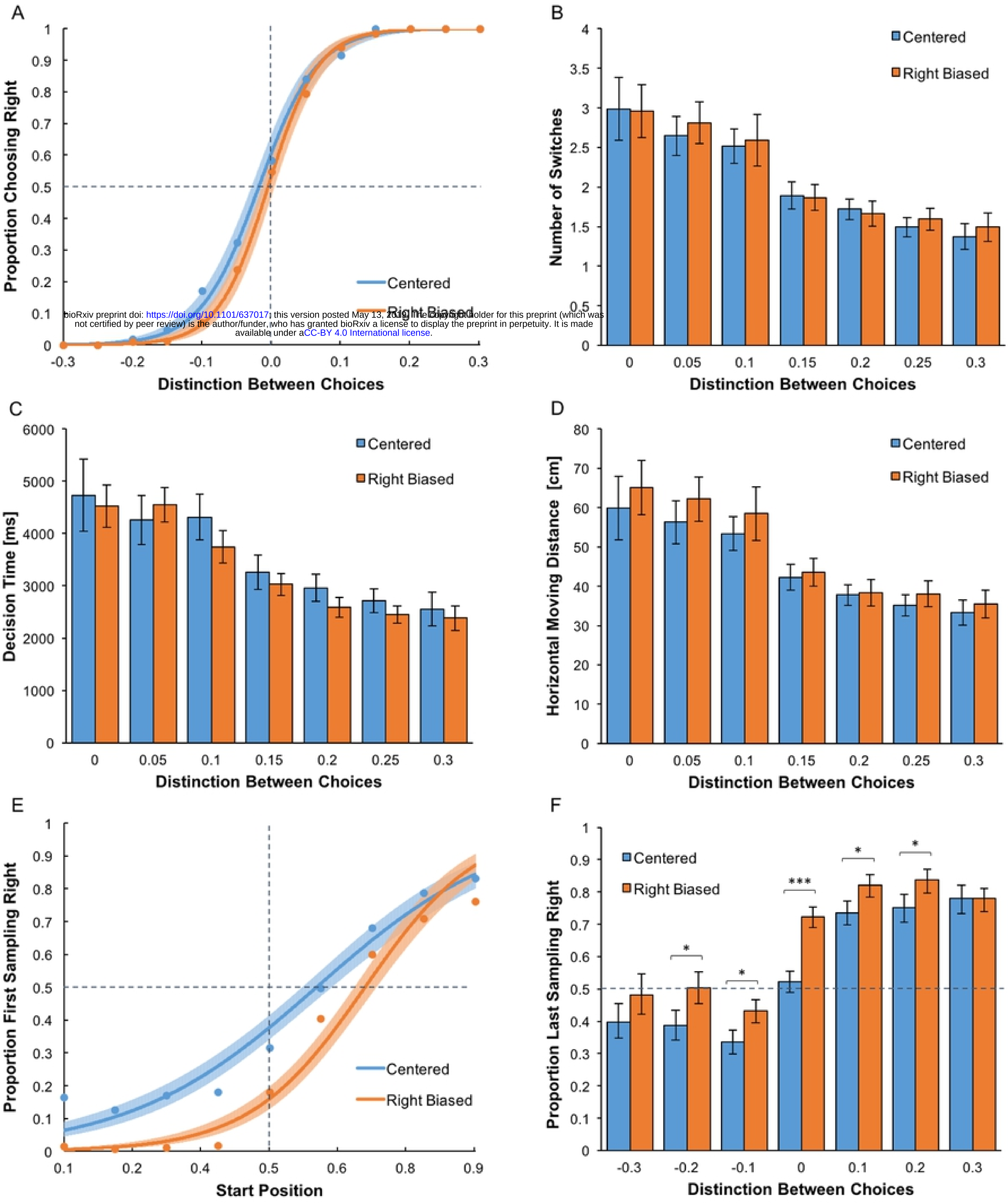


Trials (Sorted by Start Position)
Time [ms]
1 (Right)
0 (Left)
0
10
20
30
40
50
60
2000
4000
6000
8000
10000
12000
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9

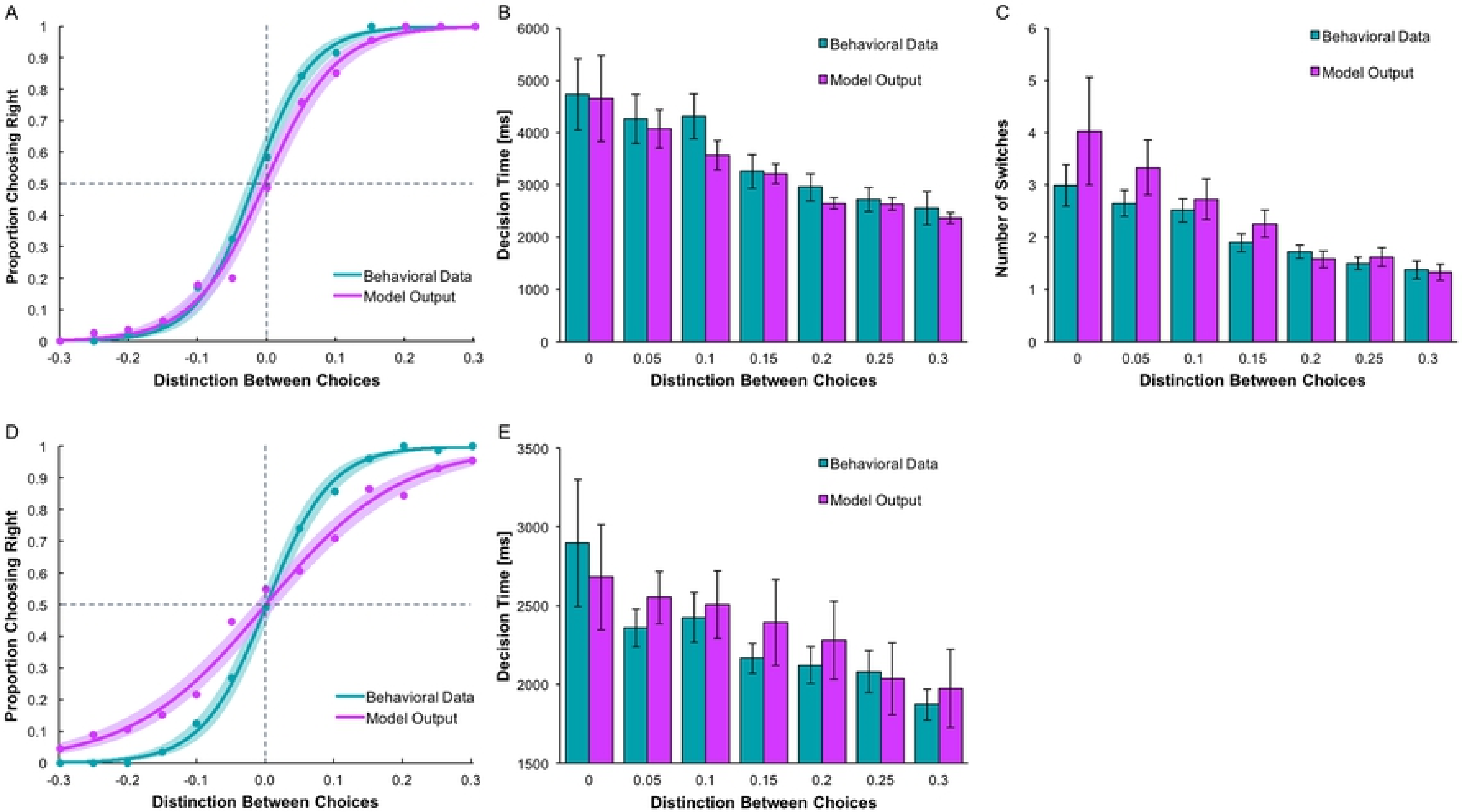
Figure


A
B
C
Distinction Between Choices
0.2 ~ 0.3
0.1 ~ 0.2
0.0 ~ 0.1
Percentage [%]
45
40
35
30
25
20
15
10
5
0
1 2 3 4 5 6 7 8 9 10
Number of Switches
Decision Time [ms]
16000
14000
12000
10000
8000
6000
4000
2000
0
1 2 3 4 5 6 7 8 9 10
Number of Switches
Horizontal Moving Distance [cm]
250
200
150
100
50
0
1 2 3 4 5 6 7 8 9 10
Number of Switches

Figure

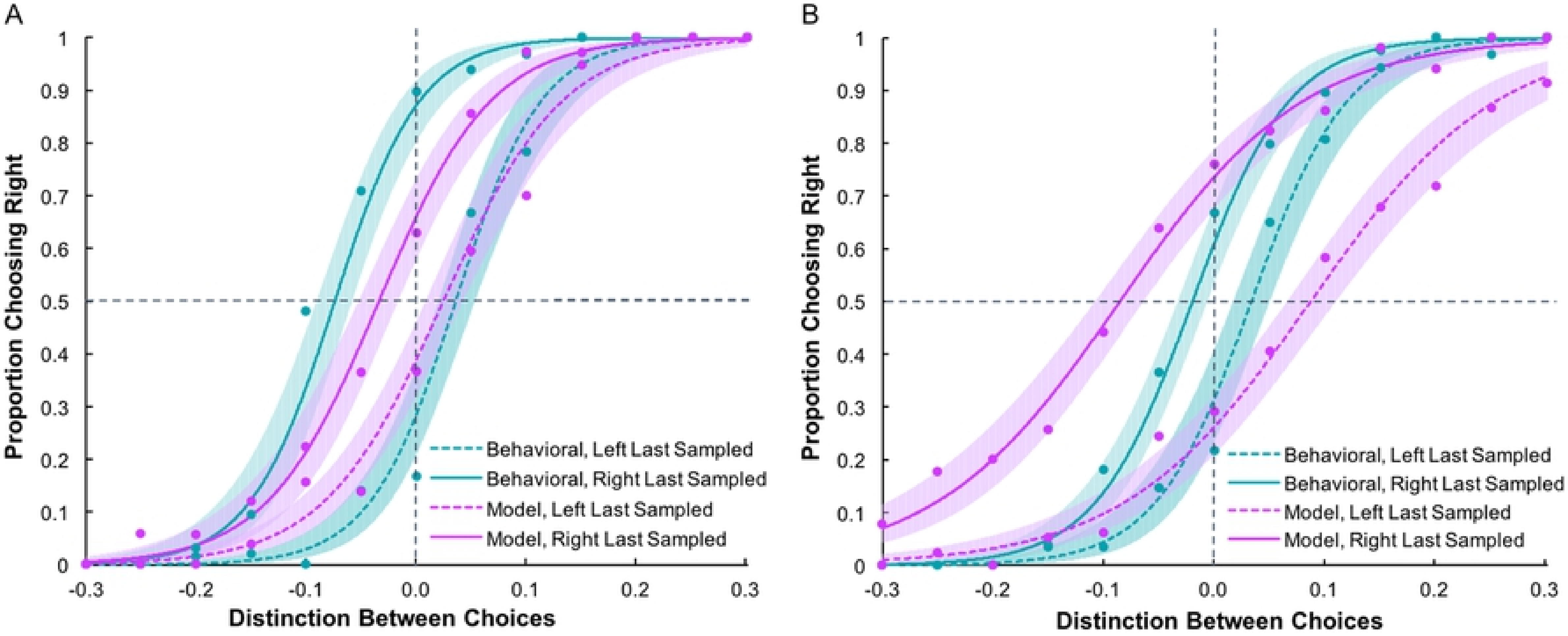

A
Proportion Choosing Right
Distinction Between Choices
Centered
Right Biased
B
Number of Switches
Distinction Between Choices
Centered
Right Biased
C
Decision Time [ms]
Distinction Between Choices
Centered
Right Biased
D
Horizontal Moving Distance [cm]
Distinction Between Choices
Centered
Right Biased
E
Proportion First Sampling Right
Start Position
Centered
Right Biased
F
Proportion Last Sampling Right
Distinction Between Choices
Centered
Right Biased
*
*
***
*
*

Figure

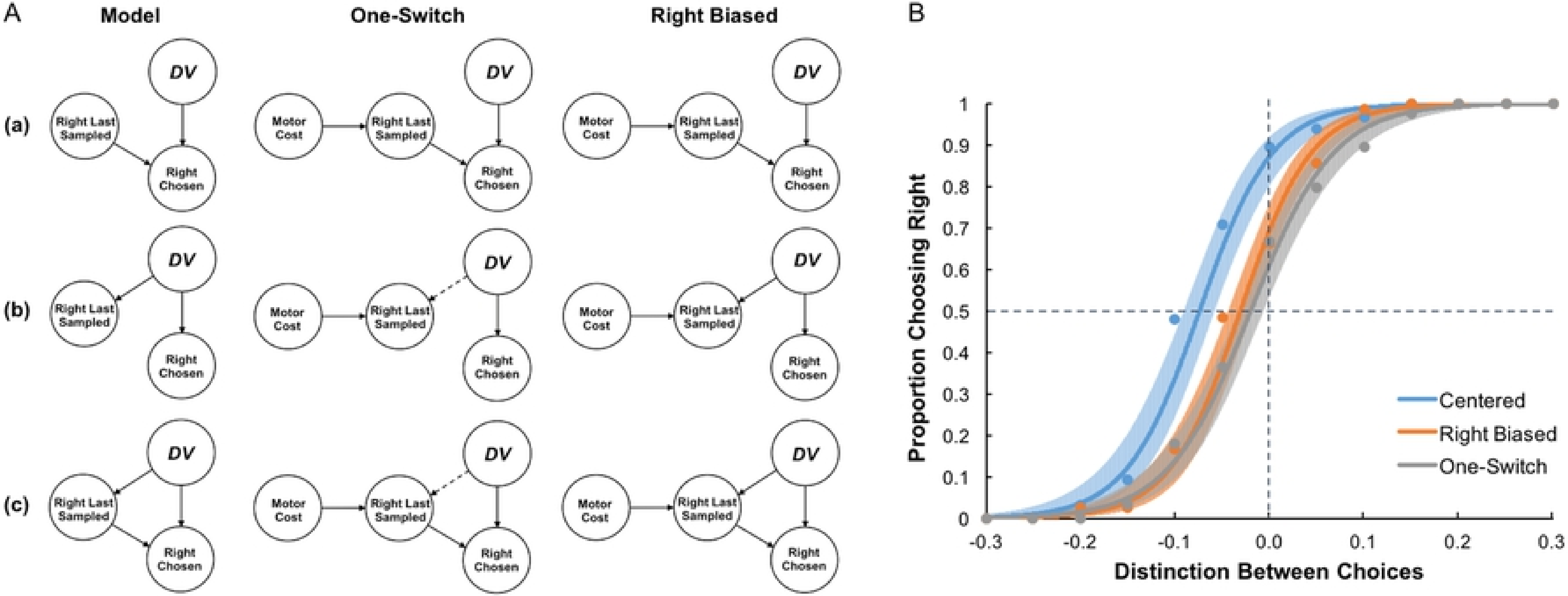


A
B
C
D
E
Proportion Choosing Right
Decision Time [ms]
Number of Switches
Distinction Between Choices
Behavioral Data
Model Output
-0.3
-0.2
-0.1
0.0
0.1
0.2
0.3
0
0.05
0.15
0.25
1000
2000
3000
4000
5000
6000
1500
2500
3500

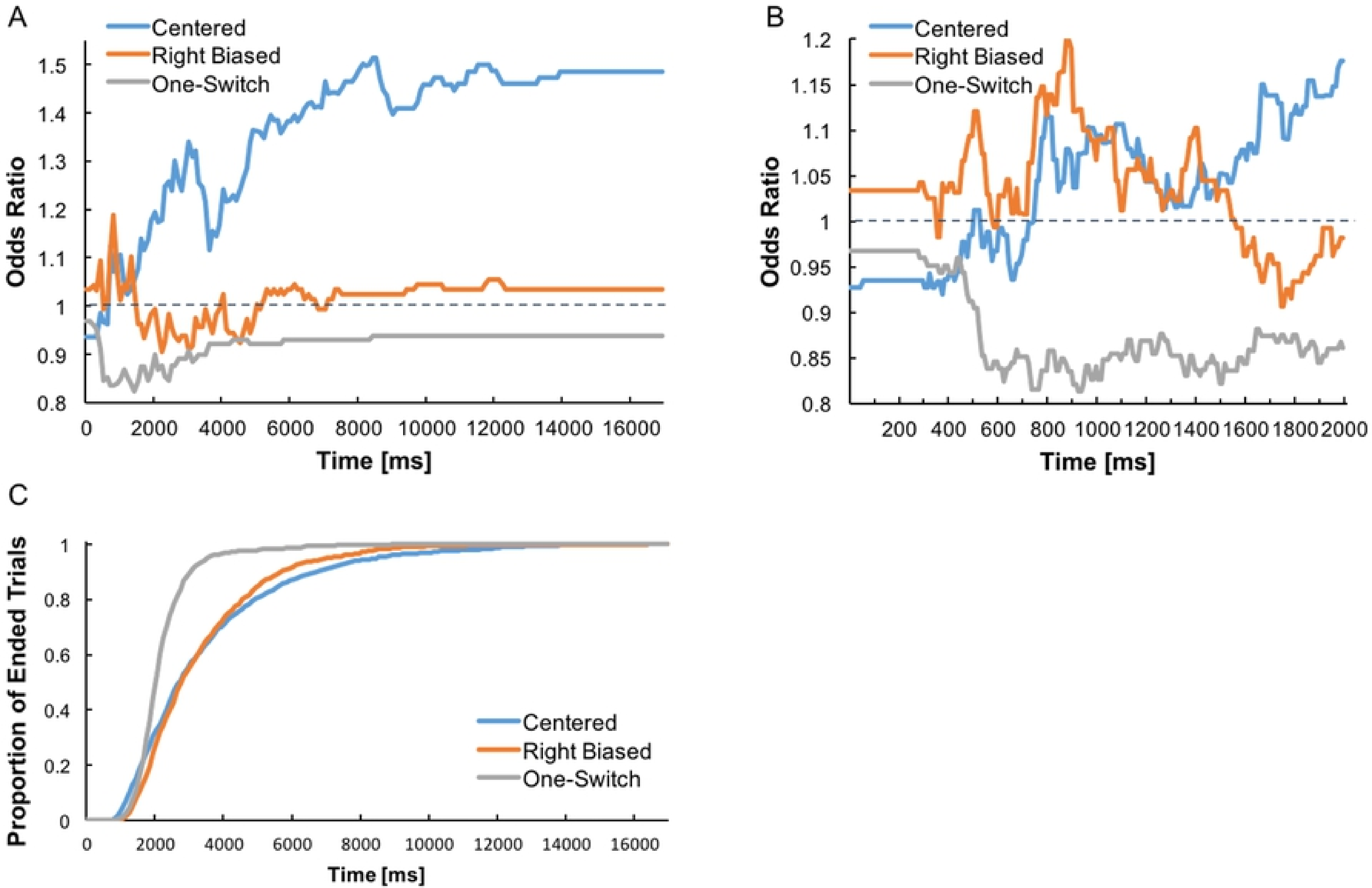
Figure


A
B
Proportion Choosing Right
Distinction Between Choices
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.3
-0.2
-0.1
0.0
0.1
0.2
0.3
Behavioral, Left Last Sampled
Behavioral, Right Last Sampled
Model, Left Last Sampled
Model, Right Last Sampled

Figure

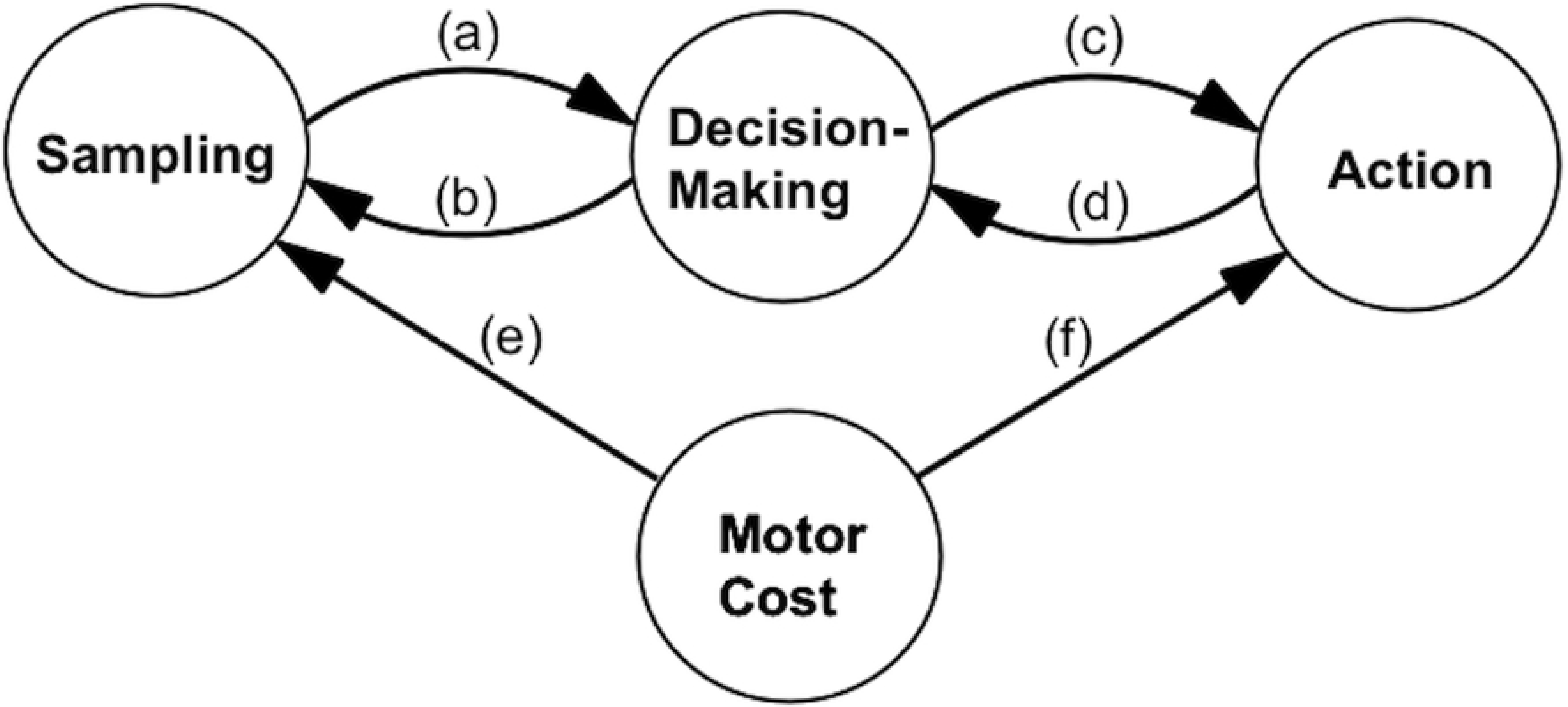

A
Model
One-Switch
Right Biased
(a)
(b)
(c)
DV
Right Last Sampled
Right Chosen
Motor Cost
B
Proportion Choosing Right
Distinction Between Choices
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.3
-0.2
-0.1
0.0
0.1
0.2
0.3
Centered
Right Biased
One-Switch

Figure



A
Centered
Right Biased
One-Switch
Odds Ratio
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
0
2000
4000
6000
8000
10000
12000
14000
16000
Time [ms]
B
Centered
Right Biased
One-Switch
Odds Ratio
1.2
1.15
1.1
1.05
1
0.95
0.9
0.85
0.8
200
400
600
800
1000
1200
1400
1600
1800
2000
Time [ms]
C
Proportion of Ended Trials
1
0.8
0.6
0.4
0.2
0
0
2000
4000
6000
8000
10000
12000
14000
16000
Time [ms]
Centered
Right Biased
One-Switch

Figure



Figure