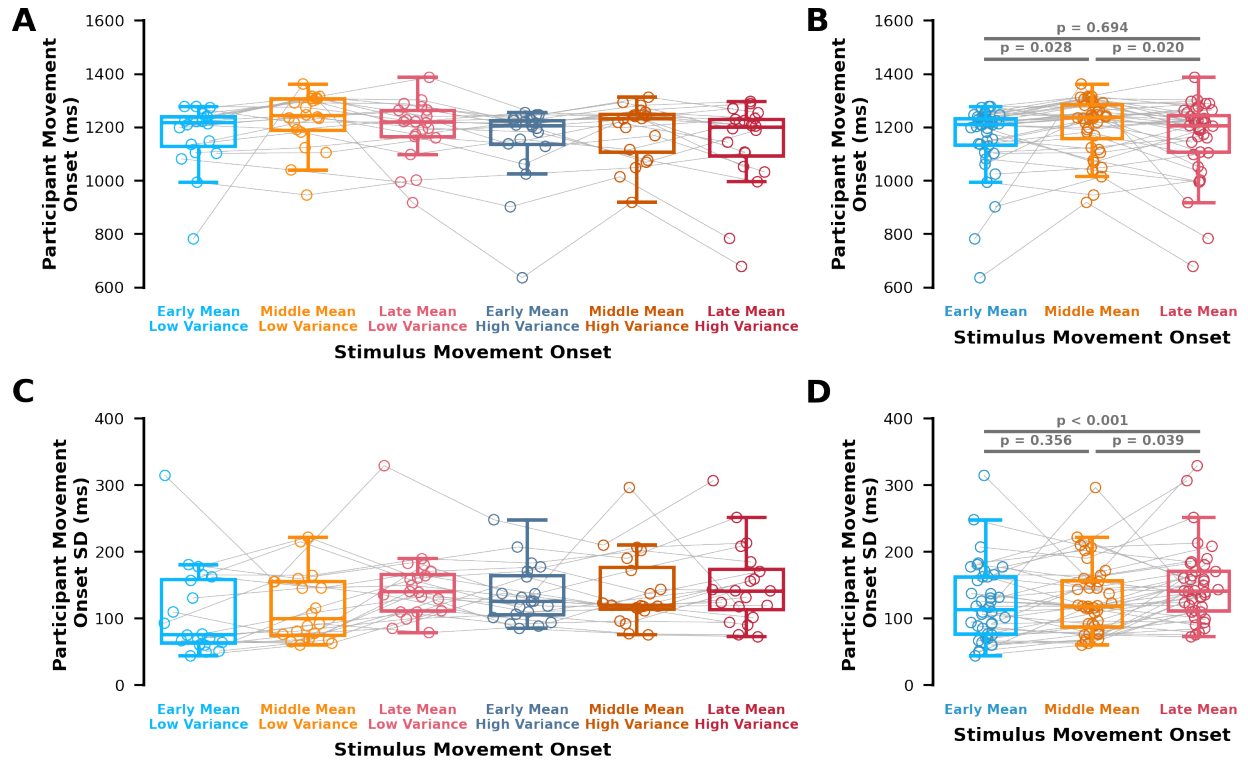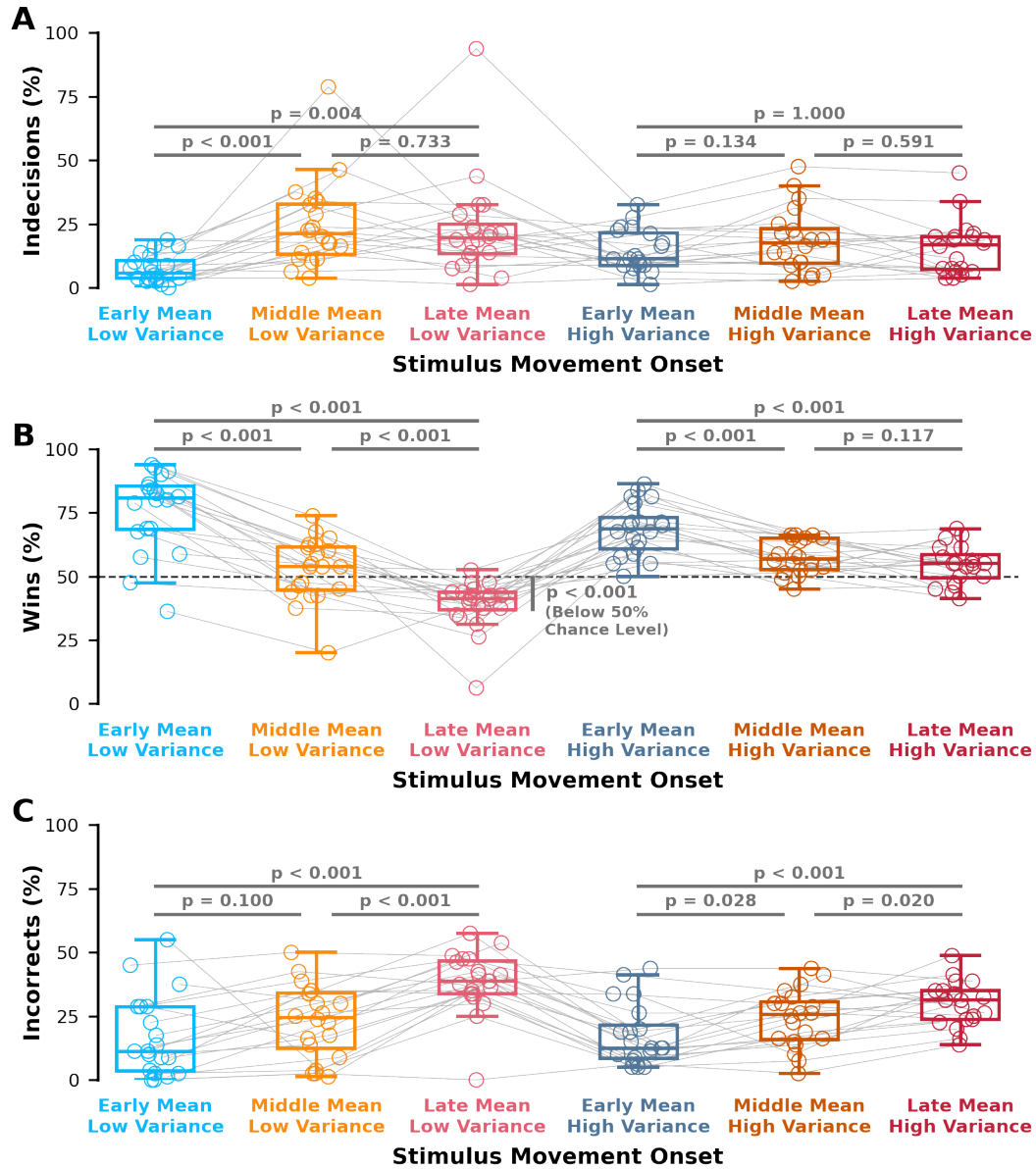# Supplementary

Supplementary A: Low and High Variance Results

Supplementary Figure 1: Timing Behaviour. A) *Average participant movement onset (y-axis) for each experimental condition (x-axis). We found a significant main effect of stimulus movement onset mean (F[1.55,29.48] = 4.36, p = 0.030) and variance (F[1.00,19.00], p = 0.017)) on participant movement onset. There was no significant interaction (F[1.66,31.47], p = 0.565)* **B)** *Corresponding participant movement onset (y-axis) for the three different mean stimulus onsets (x-axis) when collapsed across variance. During the early mean conditions, participants had a high probability of reacting to the stimulus and reaching a target within the time constraint. For the middle mean conditions, participants often waited longer to react and had a later guess than the early mean conditions. Waiting longer to react and/or late guessing led to later movement onset. In the late mean condition, participants waited to react to the stimulus, but ended up guessing a majority of the time (see* **Supplementary Figure 6**). *The combination of waiting for the stimulus and eventually guessing, led to an earlier movement onset compared to the middle mean condition. For both the middle mean and late mean conditions, late guessing often led to indecisions (see* **Fig. 2**). **C)** *Participant movement onset standard deviation (y-axis) for each experimental condition (x-axis). We found a significant main effect of mean (F[1.38, 26.28], p = 0.018) and variance (F[1.00,19.00], p < 0.001) on participant movement onset standard deviation There was no significant interaction between stimulus movement onset mean and variance (F[1.98, 37.58], p = 0.097)* **D)** *Corresponding participant movement onset standard deviation (y-axis) for the three different mean onsets (x-axis), when collapsed across variance. In the late mean conditions, waiting to react and then guessing led to a larger movement onset standard deviation compared to the early mean and middle mean conditions. Box and whisker plots display the 25th, 50th, and 75th percentiles. Open circles and connecting lines represent individual data.*
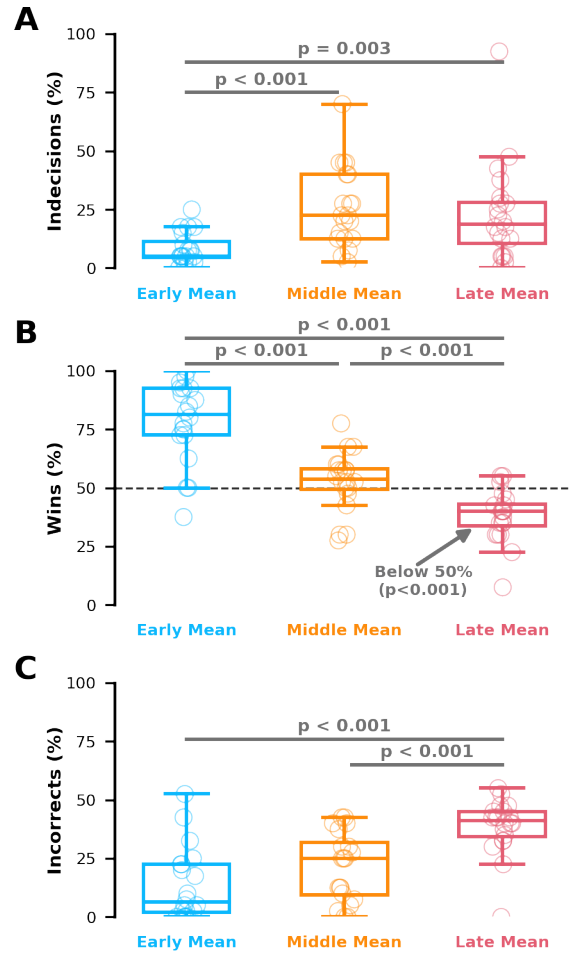
Supplementary Figure 2: Trial Outcomes. A) *Indecisions (%)* ***B)*** *Wins (%), and* ***C)*** *Incorrects (%) for each condition.* ***A)*** *We found that the middle mean low variance and late mean low variance condition had a significantly greater number of indecisions compared to the early mean low variance condition. That is, in the middle mean low variance and late mean low variance conditions, participants often waited to react to the stimulus but ended up guessing late. These late guesses often led to indecisions.* ***B)*** *Interestingly, we also found that the average win percentage (41%) was significantly below the 50% chance level (p < 0.001) in the late mean low variance condition, clearly demonstrating suboptimal behaviour. Critically, participants would have earned more points if they had simply guessed early on all trials, rather than attempting to react to the stimulus. Collectively, these results show that participants were suboptimal decision makers that led to excessively indecisive behaviour.*

Supplementary B: First Half and Second Half Data Trends
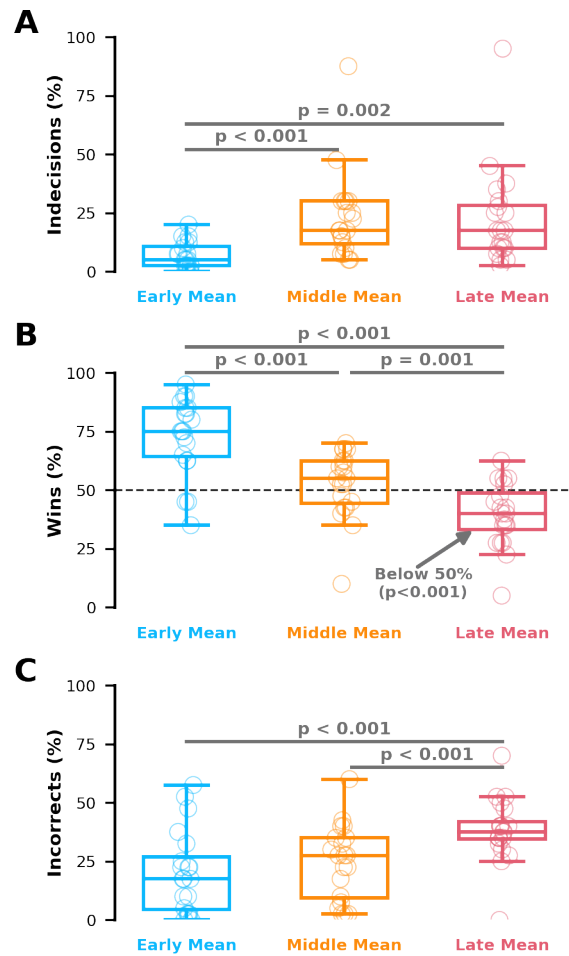
Supplementary Figure 3: Outcome Metrics for First Half of Trials. *A) Indecisions (%) **B)** Wins (%), and* ***C)*** *Incorrects (%) for the first half of trials. Here we show that the significant differences between conditions are the same for the first and second half of trials (**Supplementary Figure 4**). The same trends for the first half and second half of trials indicates that participants determined their timing strategy early on in each condition and there was a negligible effect of learning.*

Supplementary Figure 4: Outcome Metrics for Second Half of Trials A) *Indecisions (%)* **B)** *Wins (%), and* **C)** *Incorrects (%) for the second half of trials. Here we show that the significant differences between conditions are the same for the first half (***Supplementary Figure 3***) and second half of trials. The same trends for the first half and second half of trials indicates that participants determined their timing strategy early on in each condition and there was a negligible effect of learning.*

Supplementary C: Optimal Models

We tested three different models to investigate the ability of participants to maximize reward during **Experiment 1**: i) No Switch Time Model, ii) Full Switch Time Model and iii) Partial Switch Time Model (**Fig. 2**). Each model represents a different hypothesis on how humans time their decisions, which we address further below. Intuitively, participants should react to the stimulus on trials where it moved earlier in time and guess on trials where it moved later in time. That is, reacting to early stimulus movement onsets ensures they can select the correct target. Likewise, guessing on late stimulus movement onsets affords the participant a 50% chance of selecting the correct target. However, if participants wait too long to react to a late stimulus movement onset, then they might make too many indecisions and fail to maximize reward. We modelled the time to switch from reacting to guessing as an optimal transition problem. This differs from past models that have used a similar Bayesian framework, which has beenused to determine reach aim (Trommershäuser et al., 2003) and reach timing (Hudson et al., 2008). Here a model represents a decision-maker that selects a transition time, τ. This transition time determines when to stop waiting to react to the stimulus and switch to guessing one of the two targets. The optimal transition time is determined from a decision policy that maximizes reward, given task constraints (i.e. stimulus movement onset distribution and time constraint), and knowledge of sensorimotor delays and uncertainties.

Model Parameters

Here we define the parameters used for the three models. Note that not all the parameters are used in each model, which we specify further below and in **Fig. 2**. The Response Time parameters has both a mean (μ_{rt}) and uncertainty (σ_{rt}) that represents the delay between observing the stimulus movement onset to initiating a movement. Neuromechanical Delay is the mean (μ_{nmd}) and uncertainty (σ_{nmd}) of the time between a

30 volitional decision to move and movement onset. Movement Time represents the mean

31 (μ_{mt}) and uncertainty (σ_{mt}) of the delay between movement onset and reaching a target.

32 Stimulus Movement onset is knowledge of the mean (μ_S) and uncertainty (σ_S) of the

33 stimulus's movement onset distribution. Timing uncertainty (σ_τ) is the participant

34 uncertainty around the intended transition time, τ. Switch Time represents the

35 additional delay (μ_{switch}) and uncertainty (σ_{switch}) of switching from reacting to guessing.

36 All probability distributions are assumed to be normally distributed with a mean μ and

37 standard deviation σ. Each of our three models has a different set of known and

38 unknown parameters. A model decision policy has full knowledge of known parameters,

39 and no or partial knowledge of unknown parameters when determining the optimal

40 decision time.

41 *No Switch Time Model*

42 The No Switch Time Model had the following known parameters: response time mean

43 and uncertainty, movement time mean and uncertainty, neuromechanical delay mean

44 and uncertainty, timing uncertainty, and stimulus movement onset. This model had no

45 unknown parameters. Importantly, the No Switch Time Model did not include the

46 switch time mean and uncertainty in neither the known nor the unknown parameter sets.

47 The No Switch Time Model reflects the hypothesis that there is no additional delay and

48 uncertainty when switching from reacting to guessing.

49 *Full Switch Time Model*

50 The Full Switch Time Model had the following known parameters: response time mean

51 and uncertainty, neuromechanical delay mean and uncertainty, movement time mean

52 and uncertainty, stimulus movement onset, timing uncertainty, and switch time mean

53 and uncertainty. This model did not have any unknown parameters. The Full Switch

54 Time Model reflects the hypothesis that participants fully account for a delay and

55 uncertainty associated with switching from reacting to guessing.

₅₆ *Partial Switch Time Model*

₅₇ The Partial Switch Time Model had the following known parameters: response time

₅₈ mean and uncertainty, neuromechanical delay mean and uncertainty, movement time

₅₉ mean and uncertainty, and stimulus movement onset. This model had the following

₆₀ unknown parameters: switch time mean and uncertainty, and timing uncertainty. The

₆₁ Partial Switch Time Model reflects our hypothesis that participants can only partially

₆₂ account for the delay and uncertainties associated with guessing.

General Formulation for the Models

₆₄ We begin by defining the general normal probability density function and cumulative

₆₅ density function:

$$X \sim \mathcal{N}(\mu, \sigma) \tag{1}$$

₆₆

$$f_X(x; \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \tag{2}$$

₆₇

$$F_X(b) = P(X \leq b) = \int_{-\infty}^{b} f_X(x; \mu, \sigma)\,dx \tag{3}$$

₆₈ X is the random variable drawn from a normal distribution $\mathcal{N}$ with some mean and

₆₉ standard deviation. $f_X(x; \mu, \sigma)$ is the normal probability density function over the

₇₀ variable x, with a mean (μ) and standard deviation (σ). $F_X(b)$ is the normal cumulative

₇₁ density, which is the integral of the probability density function $f_X(x; \mu, \sigma)$ from $-\infty$ to b.

₇₂ Throughout, capitalized variables denote normally distributed random variables.

₇₃ Additionally, lowercase variables such as x refer to the realization of the random

₇₄ variable X. The lowercase notation simply indicates that the value is known and is not a

₇₅ random variable.

₇₆ Next we define the mean and standard deviation of the participant movement onset

₇₇ separately for reaction decisions and guess decisions. We begin by defining S as the

random variable drawn from the stimulus movement onset distribution (**Eq. 4**) and T as the random variable drawn from the transition time distribution (**Eq. 5**).

$$S \sim \mathcal{N}(\mu_S, \sigma_S) \tag{4}$$

$$T \sim \mathcal{N}(\tau, \sigma_\tau) \tag{5}$$

Consider s and t as the realizations of random variables S and T for a single trial. On any specific trial, a decision-maker will react if the stimulus movement onset is before the transition time (i.e., $s < t$). Conversely, the decision-maker will guess at the transition time if the stimulus has not moved by the transition time (i.e., $s > t$). Thus, the probability that a participant will react or guess depends on the participants choice of a transition time mean (τ). Specifically, the probability that the participant will react is the probability that the random variable T is greater than S.

$$P(React|\tau) = P(T > S). \tag{6}$$

The probability that the participant will guess is the probability that the random variable T is less than S.

$$P(Guess|\tau) = P(T < S). \tag{7}$$

As a result, a decision-maker only reacts to the portion of the stimulus's distribution that is prior to their transition time. Thus, the participant reacts to a truncated distribution of the stimulus movement onset. The truncated stimulus movement onset distribution is generated from only taking the random variable S if it is less than the random variable T. We can then define an indicator function ($\mathbb{1}_{s<t}$), which is equal to one if the realized value s is less than t and zero otherwise:

$$\mathbb{1}_{s<t} = \begin{cases} 1 & \text{if } s < t, \\ 0 & \text{otherwise.} \end{cases} \tag{8}$$

The mean of the truncated stimulus movement onset distribution ($\mu_{S_{react}}$) can be calculated by combining the indicator function and the method of moments. We start

97 by calculating the expected value of the random variable S, which is the integral from

98 $-\infty$ to ∞ of the value s multiplied by the probability density function $f_S(s)$.

$$\mu_S = \mathbb{E}[S] = \int_{-\infty}^{\infty} s \cdot f_S(s).ds \tag{9}$$

99 Note that the expected value of the full stimulus movement onset distribution defined

100 here is equivalent to the mean of the distribution. For the truncated stimulus movement

101 onset distribution, we only take values s if they are less than t. Since the inclusion of s

102 depends on t, we calculate the mean of the truncated stimulus movement onset

103 distribution by integrating over every possible combination of s and t. Inside the double

104 integral, we multiply the realized value s by its probability density function (i.e., $f_S(s)$).

105 We also multiply the probability density function for t (i.e., $f_T(t)$) and the indicator

106 function ($\mathbb{1}_{s<t}$). Since this double integral multiplies two gaussian probability density

107 functions and only sums values if s is less than t, we must normalize by dividing by the

108 probability that S is less than T. The mean (first moment) of the truncated stimulus

109 movement onset distribution is

$$\mu_{S_{react}} = \frac{\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} s \cdot f_S(s) \cdot f_T(t) \cdot \mathbb{1}_{s \in S} \, da dt}{P(S < T)}. \tag{10}$$

110 Similarly, we can find the standard deviation of the truncated stimulus movement onset

111 distribution, where variance is the second moment, by:

$$\sigma_{S_{react}}^2 = \frac{\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (s - \mu_{S_{react}})^2 \cdot f_S(s) \cdot f_T(t) \cdot \mathbb{1}_{s<t} \, ds \, dt}{P(S < T)}. \tag{11}$$

112 The player's movement onset distribution consists of a mix between reacting to the

113 truncated stimulus movement onset and guessing. Importantly, reacting and guessing

114 have unique delays and uncertainties. Thus, reaction decisions and guess decisions will

115 lead to unique means and uncertainties of the participant movement onset distribution.

116 The participant mean reaction movement onset ($\mu_{mo_{react}}$, **Eq. 12**) is the truncated

117 stimulus movement onset mean ($\mu_{S_{react}}$) plus the participant mean response time (μ_{rt}).

118 Likewise, the standard deviation of participant reaction movement onset ($\sigma_{mo_{react}}$, **Eq.**

119 **13**) is the square root of the variance of the truncated stimulus movement onset

120 distribution ($\sigma^2_{S_{react}}$) plus the participant response time variance (σ^2_{rt}).

$$\mu_{mo_{react}} = \mu_{S_{react}} + \mu_{rt} \tag{12}$$

121

$$\sigma_{mo_{react}} = \sqrt{\sigma^2_{S_{react}} + \sigma^2_{rt}} \tag{13}$$

122 Here, μ_{rt} represents the time to process the stimulus movement plus the

123 neuromechanical delay (μ_{nmd}). For the No Switch Time Model, the participant mean

124 guess movement onset ($\mu_{mo_{guess}}$, **Eq. 14**) is the sum of the participant transition time τ

125 and the mean neuromechanical delay μ_{nmd}. The participant standard deviation guess

126 movement onset ($\sigma_{mo_{guess}}$) is the square root of the sum of the timing variance σ^2_τ and

127 neuromechanical delay variance σ^2_{nmd} (**Eq. 15**).

$$\mu_{mo_{guess}} = \tau + \mu_{nmd} \tag{14}$$

128

$$\sigma_{mo_{guess}} = \sqrt{\sigma^2_\tau + \sigma^2_{nmd}} \tag{15}$$

129 Crucially, for the Full Switch Time Model and Partial Switch Time Model, the mean and

130 standard deviation of the guess movement onset includes the switch time mean and

131 uncertainty,

$$\mu_{mo_{guess}} = \tau + \mu_{nmd} + \mu_{switch} \tag{16}$$

132

$$\sigma_{mo_{guess}} = \sqrt{\sigma^2_\tau + \sigma^2_{nmd} + \sigma^2_{switch}} \tag{17}$$

133 For both the Full Switch Time Model and Partial Switch Time Model, the switch time

134 mean and uncertainty influence the model outputs. However, the decision policy of the

135 Full Switch Time Model has perfect knowledge of the switch time, while the decision

136 policy of the Partial Switch Time Model has imperfect knowledge of the switch time.

137 Further below (see Model Fitting), we address how we estimate the amount of

138 imperfect knowledge for the Partial Switch Time Model.

139 We define the react target reach time mean ($\mu_{reach_{react}}$) and standard deviation

140 $(\sigma_{reach_{react}})$, and the guess target reach time mean $(\mu_{reach_{guess}})$ and standard deviation

141 $(\sigma_{reach_{guess}})$ as

$$\mu_{reach_{react}} = \mu_{mo_{react}} + \mu_{mt} \tag{18}$$

$$\sigma_{reach_{react}} = \sqrt{\sigma^2_{mo_{react}} + \sigma^2_{mt}} \tag{19}$$

$$\mu_{reach_{guess}} = \mu_{mo_{guess}} + \mu_{mt} \tag{20}$$

$$\sigma_{reach_{guess}} = \sqrt{\sigma^2_{mo_{guess}} + \sigma^2_{mt}}. \tag{21}$$

142 To obtain the probability of reaching the target given the participant has either reacted

143 $(X_{reach_{react}})$ or guessed $(X_{reach_{guess}})$, we need to define a random variable for the

144 distribution of target reach times according to

$$X_{reach_{react}} \sim \mathcal{N}(\mu_{reach_{react}}, \sigma_{reach_{react}}) \tag{22}$$

$$X_{reach_{guess}} \sim \mathcal{N}(\mu_{reach_{guess}}, \sigma_{reach_{guess}}) \tag{23}$$

145 We can then define the probability that the participant will reach one of the two targets

146 before the time constraint of 1500ms given they react $(P(Reach|React))$ or guess

147 $(P(Reach|Guess))$:

$$P(Reach|React) = P(X_{reach_{react}} < 1500) \tag{24}$$

148

$$P(Reach|Guess) = P(X_{reach_{guess}} < 1500) \tag{25}$$

149 We can now define the conditional probabilities for three outcome metrics: indecision,

150 win, and incorrect. The conditional probability of an indecision given the participant has

151 reacted $(P(Indecision|React))$ or guessed $(P(Indecision|Guess))$ follows immediately

152 from **Eqs. 24-25**. An indecision is simply the probability that the participant does not

153 reach the target within the time constraint:

$$P(Indecision|React) = 1 - P(Reach|React) \tag{26}$$

154

$$P(Indecision|Guess) = 1 - P(Reach|Guess) \tag{27}$$

To define a win or incorrect trial, we need the conditional probability of selecting the correct target given the participant has either reacted ($P(Correct|React)$) or guessed ($P(Correct|Guess)$). The probability of selecting the correct target when the participant reacts is 100% (**Eq. 28**). The probability of selecting the correct target when the participant guesses is 50% (**Eq. 29**).

$$P(Correct|React) = 1.0 \tag{28}$$

$$P(Correct|Guess) = 0.5 \tag{29}$$

The conditional probability the participant wins given they react ($P(Win|React)$) or guess ($P(Win|Guess)$) is the probability that they reach the target within the time constraint, and they select the correct target:

$$P(Win|React) = P(Reach|React) \cdot P(Correct|React) \tag{30}$$

$$P(Win|Guess) = P(Reach|Guess) \cdot P(Correct|Guess) \tag{31}$$

The conditional probability the participant is incorrect given they react ($P(Incorrect|React)$) or guess ($P(Incorrect|Guess)$) is the probability that they reach the target within the time constraint and they select the wrong target:

$$P(Incorrect|React) = P(Reach|React) \cdot (1 - P(Correct|React)) \tag{32}$$

$$P(Incorrect|Guess) = P(Reach|Guess) \cdot (1 - P(Correct|Guess)) \tag{33}$$

Finally, we define the final probability of wins ($P(Win|\tau)$), indecisions ($P(Indecision|\tau)$), and incorrects ($P(Incorrect|\tau)$), by considering their and their associated conditional probabilities (**Eq. 26-33**) and the probability of reaching and guessing given a

172 transition time (τ), as

$$
\begin{aligned}
P(Win|\tau) =\ &P(React|\tau) \cdot P(Win|React) \\
&+ P(Guess|\tau) \cdot P(Win|Guess)
\end{aligned}
\tag{34}
$$

$$
\begin{aligned}
P(Indecision|\tau) =\ &P(React|\tau) \cdot P(Indecision|React) \\
&+ P(Guess|\tau) \cdot P(Indecision|Guess)
\end{aligned}
\tag{35}
$$

$$
\begin{aligned}
P(Incorrect|\tau) =\ &P(React|\tau) \cdot P(Incorrect|React) \\
&+ P(Guess|\tau) \cdot P(Incorrect|Guess).
\end{aligned}
\tag{36}
$$

173 *Decision Policy*

174 For each model, the goal of the decision policy is to find the optimal transition time that

175 maximizes expected reward. The reward on a particular trial for wins (R_{win}), indecisions

176 ($R_{indecision}$), and incorrects ($R_{incorrect}$) is,

$$
R_{win} = 1
\tag{37}
$$

177

$$
R_{indecision} = 0
\tag{38}
$$

178

$$
R_{incorrect} = 0.
\tag{39}
$$

179 The expected reward is defined as the reward of a trial outcome multiplied by the

180 probability of that outcome, which is

$$
\begin{aligned}
\mathbb{E}[R|\tau] =\ &P(Win|\tau) \cdot R_{Win} \\
&+ P(Incorrect|\tau) \cdot R_{Incorrect} \\
&+ P(Indecision|\tau) \cdot R_{Indecision}.
\end{aligned}
\tag{40}
$$

181 The decision policy uses known parameters to select an optimal transition time τ^* that

182 maximizes expected reward:

$$
\tau^* = \underset{\tau}{argmax}[\mathbb{E}(R|\tau)].
\tag{41}
$$

Model Parameter Estimation and Fitting Procedure

As a reminder, we had three models: No Switch Time Model, Full Switch Time Model, and Partial Switch Time Model. Each of these models had full knowledge of the reaction time mean and standard deviation, neuromechanical delay mean and standard deviation, movement time mean and standard deviation, and the stimulus movement onset distribution. These parameter values were estimated from experimental data by bootstrapping the meansfrom the response time experiment (μ_{rt}, σ_{rt}), timing experiment (σ_τ), and **Experiment 1** (μ_{mt}, σ_{mt}). We describe the bootstrap procedure below. Neuromechanical delay (μ_{nmd}) and uncertainty (σ_{nmd}) were estimated from prior literature(Bruce et al., 1985; Norman & Komi, 1979; Rossini & Rossi, 1998).

We used both a warm-start initialization and bootstrap procedure (see below) to determine the switch time mean (μ_{switch}) and uncertainty (σ_{switch}), as well as the decision policy's knowledge of the switch time mean ($\hat{\mu}_{switch}$), switch time uncertainty ($\hat{\sigma}_{switch}$), and timing uncertainty ($\hat{\sigma}_\tau$).

Warm-Start Initialization

The fitting procedure for the Full Switch Time Model and Partial Switch Time Model began with a "warm-start" to find an initial set of $\mu_{switch}, \sigma_{switch}, \hat{\mu}_{switch}, \hat{\sigma}_{switch}$, and $\hat{\sigma}_\tau$ (Roth et al., 2023, 2024). Here the remaining parameters estimated from experimental data were set as the group level means. We found the best-fit parameters that led to the lowest loss between model outputs ($Model_{i,j}$) and group data means ($Data_{i,j}$) according to

$$\mathcal{L} = \sum_{i=1}^{6} \sum_{j=1}^{5} \frac{|Data_{i,j} - Model_{i,j}|}{Data_{i,j}}, \tag{42}$$

where i corresponds to experimental condition and j corresponds to each dependent measure (i.e., movement onset, standard deviation of participant movement onset, wins, indecisions, and incorrects). The fitting procedure was repeated 1,000 times to avoid local minimums. From these 1,000 optimizations, we used the set of parameters

208 that resulted in the lowest loss as the initial guess for our bootstrap procedure. Model

209 fitting was performed using the Powell algorithm in the Minimize function from the

210 Scipy Python library.

211 *Bootstrap Procedure*

212 In the bootstrap procedure we randomly sampled participants with replacement 10,000

213 times(Cashaback et al., 2017, 2019; Roth et al., 2023, 2024). We used the mean of the

214 bootstrapped participant data for each of the parameter values that were estimated

215 from data. For each bootstrap iteration, the optimization process selected the free

216 parameters for the Full Switch Time Model (μ_{switch}, σ_{switch}) and Partial Switch Time

217 Model (μ_{switch}, σ_{switch}, $\hat{\mu}_{switch}$, $\hat{\sigma}_{\tau}$, $\hat{\sigma}_{\tau}$) that minimized the loss function (**Eq. 44**).

218 **Model Parameter Values**

219 Here we report the mean and 95% confidence intervals for the bootstrapped model

220 parameters. For each parameter, each model had a value that determined the model

221 outputs and a value that the decision policy used to select τ. The No Switch Time

222 Model and Full Switch Time Model were both optimal in the sense that they had perfect

223 knowledge of all parameters. That is, the value that determined model outputs was

224 equal to the value used by the decision policy. Parameter values for reaction time

225 mean, reaction time uncertainty, movement time mean, movement time uncertainty,

226 and timing uncertainty were all calculated from participant data on each bootstrap

227 iteration: reaction time mean (247.4 ms; [239.2, 256.35]), reaction time uncertainty (38.5

228 ms; [35.7, 41.4]), movement time mean (171.7 ms; [157.6, 197.2]), movement time

229 uncertainty (25.4 ms; [22.2, 28.7]), and timing uncertainty (77.8 ms; [69.4, 86.6]). The No

230 Switch Time Model had no parameters to fit, and the decision policy had full knowledge

231 of all of these parameters. The Full Switch Time Model fit the switch time mean and

232 switch time uncertainty and the decision policy had full knowledge of all parameters.

233 The bootstrapped mean of the switch time delay parameter was 0.95 ms with a 95%

234 confidence interval of [0.21, 2.20]. The bootstrapped mean of the switch time

235 uncertainty parameter was 103.20 ms with a 95% confidence interval of [97.77, 115.31].

236 The Partial Switch Time Model fit the timing uncertainty, switch time mean, switch time

237 uncertainty. Critically, this model did not have full knowledge of these parameters, so

238 the value that the decision policy used to select the optimal time was fit separately from

239 the value that was used to determine the model outputs. Note that the timing

240 uncertainty value used for model outputs is from experimental data, but this model

241 allowed the knowledge of the timing uncertainty to be a fit parameter. The values that

242 were used for model outputs were: timing uncertainty (77.83 ms; [69.4, 86.8]), switch

243 time mean (21.10 ms; [1.46, 63.71]), switch time uncertainty (134.73 ms; [111.22,

244 155.06]. The values that were used by the decision policy were: timing uncertainty (1.65

245 ms; [0.08, 4.63]), switch time mean (9.0 ms; [0.00, 16.65]), switch time uncertainty (40.4

246 ms; [34.54, 48.02]). Critically, the fitting procedure for the Partial Switch Time Model

247 selected the decision policy's values for the switch time mean, switch time uncertainty,

248 and timing certainty to be less than the values that impact the model outputs, indicating

249 that humans have imperfect knowledge of these parameters.

Supplementary D: Model Results
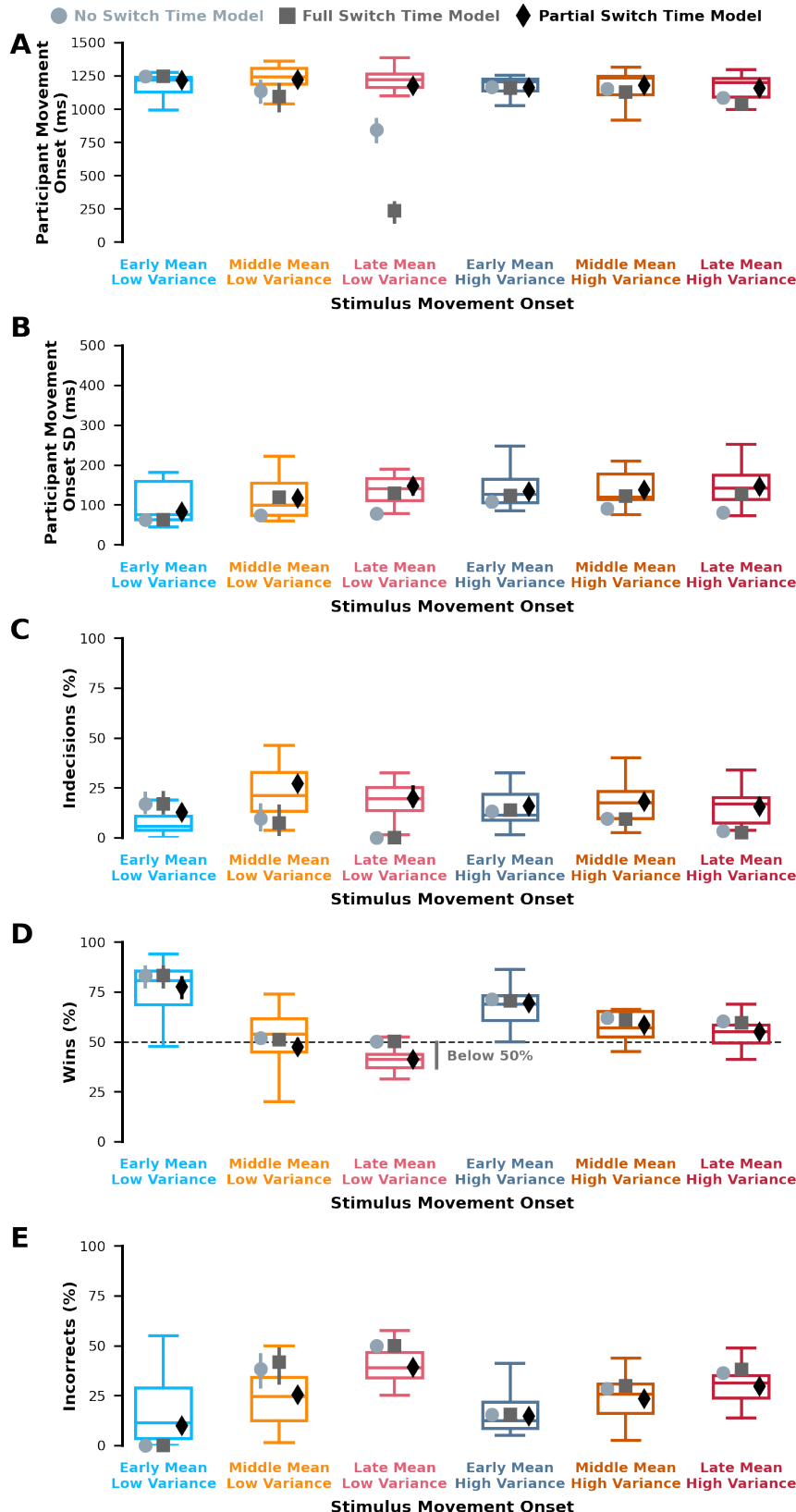
Supplementary Figure 5: Model Outputs. *Here we show model fits for the No Switch Time Model (light gray circles), Full Switch Time Model (dark gray squares), and the Partial Switch Time Model (black diamonds) for A) participant movement onset time, B) participant movement onset time standard deviation, C) indecisions, D) wins, and E) incorrects for each condition. The No Switch Time Model and Full Switch Time Model poorly predict the participant data across all five metrics for the late mean low variance and late mean high variance conditions. Conversely, the Partial Switch Time Model (black diamond) is able to accurately predict the participant data for all conditions across all metrics. As a reminder, the Partial Switch Time Model does not account for the delay and uncertainties associated with switching from reacting to guessing. Critically, in C) the Partial Switch Time Model predicts participant indecisions in the late mean low variance condition, whereas the other two models predict zero indecisions for that condition. Further, in D) the Partial Switch Time Model is the only model that aligns with the finding that participants are suboptimal and win less than 50% of trials in the late mean low variance condition. Collectively, our findings show that humans are suboptimal and excessively indecisive, which can be captured by a model that does not account for the delay and uncertainties associated with switching from reacting to guessing.*
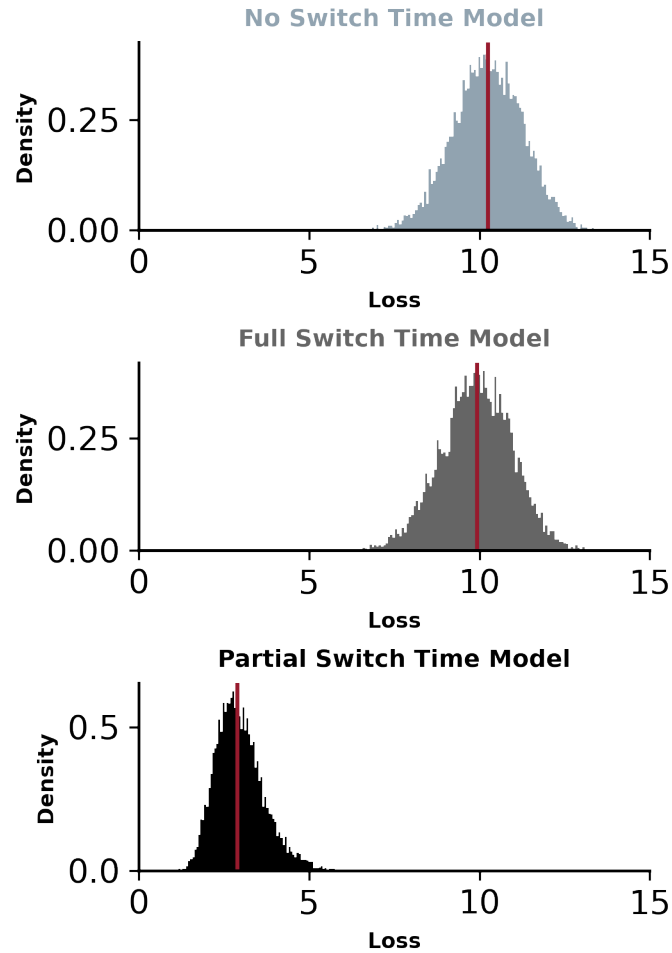
Supplementary Figure 6: Model Losses. *Here we show histograms of each of our model's bootstrapped losses. Loss was calculated as the normalized mean absolute error between the model prediction and experimental data for each of the following metrics: movement onset, movement onset standard deviation, indecisions, wins, and incorrects. The median loss is shown by the red line. The Partial Switch Time Model has the lowest loss out of the three models, suggesting that participants do not account for a delay and uncertainty when switching from reacting to guessing.*

Supplementary E: Response Time Task

For the response time task (**Supplementary Figure 7**), participants began each trial by moving their cursor (yellow circle, 1 cm diameter) into a start position (white circle, 1.5 cm diameter). Following a randomized time period (600-2400 ms drawn from a uniform distribution), one of two potential targets (white rings, 8 cm diameter) appeared on the screen. The two potential targets were positioned 16.7 cm forward relative to the start position, and either 11.1 cm to the left or right of the start position. As soon as one of the two potential targets appeared, the participant reached as fast as possible to the displayed target. Participants experienced 25 left target trials and 25 right target trials in a randomized order.

Response Time Experiment
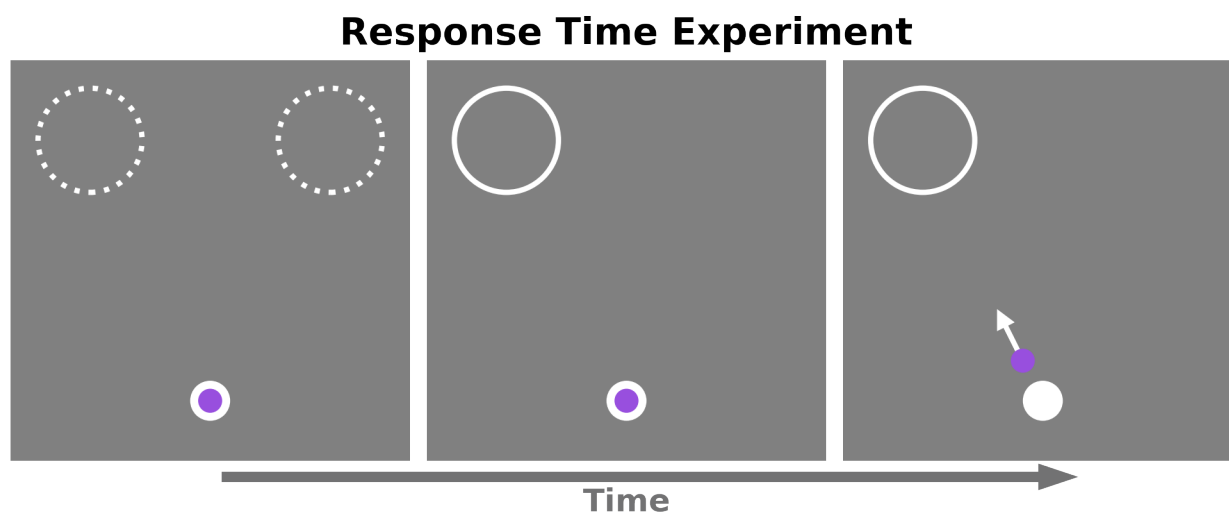
Supplementary Figure 7: Response Time Experiment. *One of two potential targets (dashed white rings; not visible to participants) would appear on the screen. Once a target appeared (solid white ring), participants were instructed to rapidly move their cursor to hit the displayed target. We used the mean and standard deviation of response times as model parameters in the optimal transition models.*

Supplementary F: Timing Uncertainty Task

To capture timing uncertainty, participants were instructed to reach into a target at a specified time of 1500 ms. Each trial began with a participant moving their cursor into a start position (white circle, 1.5 cm diameter). Following a randomized time delay (600-2400 ms drawn from a uniform distribution), they would hear a beep, a target (white ring, 8 cm diameter) appeared 17 cm forward relative to the start position, and a timing bar was displayed 10 cm below the start position. After the initial beep, participants were instructed to wait in the start position until they decided to hit the target. They were then told to make a smooth and quick movement to hit the target with their cursor at 1500 ms. They would then hear a beep at the desired time of 1500 ms. Participants performed a block of 50 trials for the timing uncertainty task with a timing bar and another block of 50 trials without a timing bar. The timing bar decreased in width over time and consequently disappeared at 1500 ms. Thus, during the trials with a timing bar the participants would have better knowledge of when they were required to hit the target. We used the data during this condition for the timing uncertainty parameter in each model, which aligned with the experimental design of **Experiment 1**. Trials where there was no timing bar were not used for subsequent analyses. We counterbalanced the blocks of trials that did or did not have the timing bar.

Timing Uncertainty Experiment
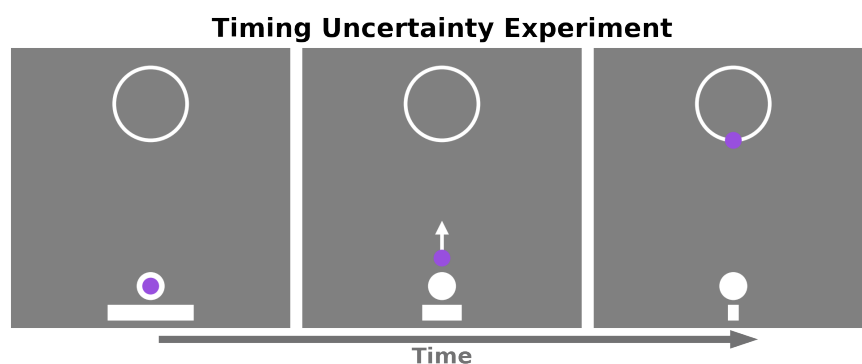
Supplementary Figure 8: Timing Uncertainty Experiment. One of two potential targets (dashed white rings; not visible to participants) would appear on the screen. Once a target appeared (solid white ring), participants were instructed to rapidly move their cursor to hit the displayed target. We used the mean and standard deviation of response times as model parameters in the optimal transition models.

Supplementary G: Guess Decisions
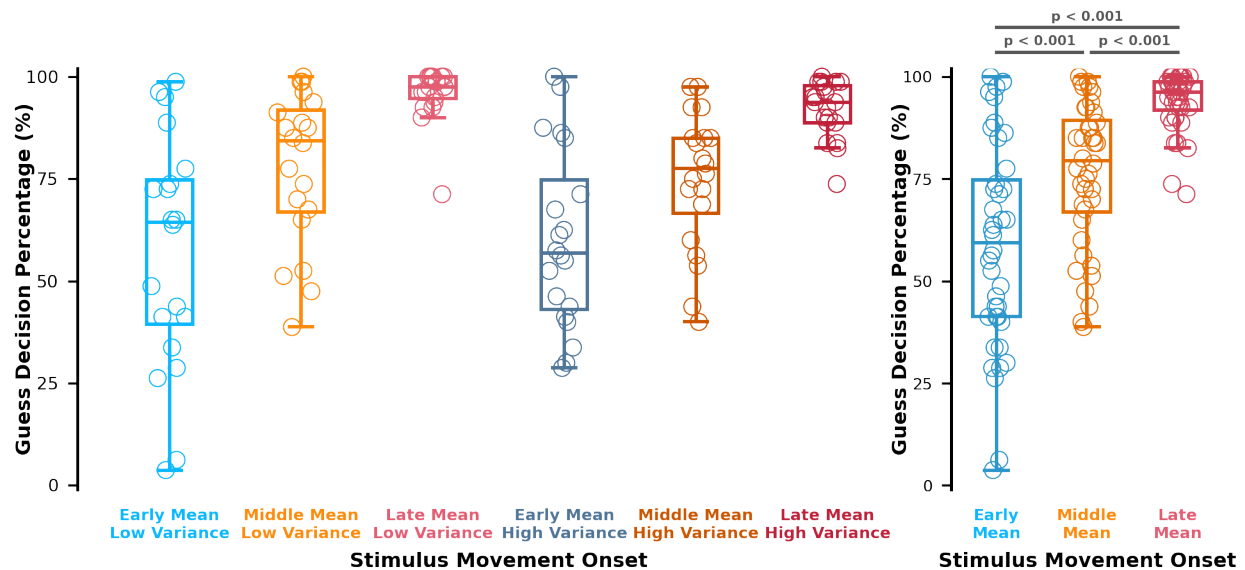
Supplementary Figure 9: Guess Decision Percentages for Experiment 1. *Estimated percentage of guess decision percentages (y-axis) for each experimental condition (x-axis). During* **Experiment 1** *participants were rewarded for successful trials and experienced a time constraint. Thus, we would expect participants to have faster response times in* **Experiment 1** *than in the Response Time task (Milstein & Dorris, 2007; Shadmehr et al., 2019). To account for this, we adjusted participant response times by subtracting 25ms from their median response time in the Response Time task. A trial was a guess decision if the difference between the stimulus movement onset and participant movement onset was less than that participant's adjusted response time. We found that participants guessed significantly more often as the stimulus's mean movement onset approached the time constraint.*

Supplementary References

Bruce, C. J., Goldberg, M. E., Bushnell, M. C., & Stanton, G. B. (1985). Primate frontal eye fields. II. Physiological and anatomical correlates of electrically evoked eye movements. *Journal of Neurophysiology*, *54*(3), 714–734. https://doi.org/10.1152/jn.1985.54.3.714

Cashaback, J. G. A., Lao, C. K., Palidis, D. J., Coltman, S. K., McGregor, H. R., & Gribble, P. L. (2019). The gradient of the reinforcement landscape influences sensorimotor learning (A. M. Haith, Ed.). *PLOS Computational Biology*, *15*(3), e1006839. https://doi.org/10.1371/journal.pcbi.1006839

Cashaback, J. G. A., McGregor, H. R., Mohatarem, A., & Gribble, P. L. (2017). Dissociating error-based and reinforcement-based loss functions during sensorimotor learning (A. A. Faisal, Ed.). *PLOS Computational Biology*, *13*(7), e1005623. https://doi.org/10.1371/journal.pcbi.1005623

Hudson, T. E., Maloney, L. T., & Landy, M. S. (2008). Optimal Compensation for Temporal Uncertainty in Movement Planning (K. J. Friston, Ed.). *PLoS Computational Biology*, *4*(7), e1000130. https://doi.org/10.1371/journal.pcbi.1000130

Milstein, D. M., & Dorris, M. C. (2007). The Influence of Expected Value on Saccadic Preparation. *The Journal of Neuroscience*, *27*(18), 4810–4818. https://doi.org/10.1523/JNEUROSCI.0577-07.2007

Norman, R. W., & Komi, P. V. (1979). Electromechanical delay in skeletal muscle under normal movement conditions. *Acta Physiologica Scandinavica*, *106*(3), 241–248. https://doi.org/10.1111/j.1748-1716.1979.tb06394.x

Rossini, P. M., & Rossi, S. (1998). Clinical applications of motor evoked potentials. *Electroencephalography and Clinical Neurophysiology*, *106*(3), 180–194. https://doi.org/10.1016/S0013-4694(97)00097-7

Roth, A. M., Calalo, J. A., Lokesh, R., Sullivan, S. R., Grill, S., Jeka, J. J.,
Van Der Kooij, K., Carter, M. J., & Cashaback, J. G. A. (2023).
Reinforcement-based processes actively regulate motor exploration along
redundant solution manifolds. *Proceedings of the Royal Society B: Biological
Sciences*, *290*(2009), 20231475. https://doi.org/10.1098/rspb.2023.1475

Roth, A. M., Lokesh, R., Tang, J., Buggeln, J. H., Smith, C., Calalo, J. A., Sullivan, S. R.,
Ngo, T., Germain, L. S., Carter, M. J., & Cashaback, J. G. (2024). Punishment
Leads to Greater Sensorimotor Learning But Less Movement Variability
Compared to Reward. *Neuroscience*, *540*, 12–26.
https://doi.org/10.1016/j.neuroscience.2024.01.004

Shadmehr, R., Reppert, T. R., Summerside, E. M., Yoon, T., & Ahmed, A. A. (2019).
Movement Vigor as a Reflection of Subjective Economic Utility. *Trends in
Neurosciences*, *42*(5), 323–336. https://doi.org/10.1016/j.tins.2019.02.003

Trommershäuser, J., Maloney, L. T., & Landy, M. S. (2003). Statistical decision theory and
trade-offs in the control of motor response. *Spatial Vision*, *16*(3-4), 255–275.
https://doi.org/10.1163/156856803322467527