Indecision under time pressure arises from suboptimal switching behaviour

Seth R. Sullivan[1], Rakshith Lokesh[4], Jan A. Calalo[2], Truc Ngo[1], John H. Buggeln[3], Adam M. Roth[2], Christopher Peters[1], Isaac Kurtzer[5], Michael J. Carter[6], Joshua G.A. Cashaback[1,2,3,6,7]

[1] Department of Biomedical Engineering, University of Delaware
[2] Department of Mechanical Engineering, University of Delaware
[3] Biomechanics and Movements Science Program, University of Delaware
[4] Department of Electrical and Computer Engineering, Northeastern University
[5] College of Osteopathic Medicine, New York Institute of Technology
[6] Department of Kinesiology, McMaster University
[7] Interdisciplinary Neuroscience Graduate Program, University of Delaware

Abbreviated Title:

Indecision arises from suboptimal switching

Correspondence:

Seth Sullivan
Biomedical Engineering
University of Delaware
Newark, DE 19711, U.S.A
Email: sethsullivan99@gmail.com

Joshua G. A. Cashaback, PhD
Biomedical Engineering
University of Delaware
STAR Campus, Room 201J
Newark, DE 19711, U.S.A
Email: cashabackjga@gmail.com

ABSTRACT

Indecisive behaviour can be catastrophic, leading to car crashes or stock market losses. Despite fruitful efforts across several decades to understand decision-making, there has been little research on what leads to indecision. Here we examined how indecisions arise under high-pressure deadlines. In our first experiment participants attempted to select a target by either reacting to a stimulus or guessing, when acting under a high pressure time constraint. We found that participants were suboptimal, displaying a below chance win percentage due to an excessive number of indecisions. Computational modeling suggested that participants were excessively indecisive because they failed to account for a time delay and temporal uncertainty when switching from reacting to guessing, a phenomenon previously unreported in the literature. In a followup experiment we provide direct evidence for a functionally relevant time delay and temporal uncertainty when switching from reacting to guessing. Collectively, our results demonstrate that humans are suboptimal and fail to account for a time delay and temporal uncertainty when switching from reacting to guessing, leading to indecisive behaviour.

₁₆ **INTRODUCTION**

₁₇ Indecisions arise from failing to decide and act upon sensory information in time, such

₁₈ as a driver failing to brake or hit the gas pedal when a traffic light turns yellow. When

₁₉ acting under high pressure time constraints, the ability to accurately time a decision is

₂₀ critical to success. The vast majority of decision-making research either does not consider

₂₁ responses made after some time constraint or simply does not permit a non-response,

₂₂ such as in the classic two-alternative forced choice paradigm.[1,2,3,4,5,6,7] Thus, despite its

₂₃ real-world ubiquity and importance, we have very little understanding of how indecisions

₂₄ arise.

₂₅ There have only been a handful of papers to examine indecisions, which involve ei-

₂₆ ther high[8] or low time pressure.[9,10,11,12,13] We recently found a high proportion of inde-

₂₇ cisions during a competitive decision-making task between two humans that observed

₂₈ each other's movements when selecting a target.[8] In this competitive scenario, the 'prey'

₂₉ attempted to end up in the same target as the 'predator' by a time constraint, while the

₃₀ predator attempted to end up in the opposite target as the prey. This task had a high

₃₁ time pressure, such that participants were awarded no points if they were indecisive by

₃₂ failing to enter either target within the time constraint. The task poses a conundrum:

₃₃ it may be advantageous to wait for future sensory information and react to an oppo-

₃₄ nent, but it could also be better to switch from reacting to guessing before the time

₃₅ constraint to avoid an indecision. Surprisingly, participants displayed a median indeci-

₃₆ sion rate of approximately 25% with an upper range close to 40% indecisions. Similar to

₃₇ others,[9,10,11,12,13] Karsilar and colleagues (2014) used a low time pressure task and found

₃₈ only 1.7% of trials were indecisions. Tasks with low time pressure are characterized by

₃₉ providing relatively strong sensory information well in advance of the time constraint

₄₀ deadline. Yet the mechanisms that give rise to indecisive behaviour, which is particularly

₄₁ relevant under common high time pressure scenarios, remains unclear.

₄₂ Humans and animals attempt to maximize reward to time, select, and indicate a de-

43 cision with a motor response.[2,14,15,16,17] To obtain more reward, it has been shown that

44 it is important to consider the inherent time delays and temporal uncertainties of the

45 nervous system.[15,16,18,19,20,21,22,23,24] Past work has shown that humans will often produce

46 nearly optimal decision times during cognitive[15,25] and motor tasks.[16,26] Other work has

47 shown suboptimal action selection or timing, which has been suggested to occur from

48 an imperfect representation of time delays or temporal uncertainties.[27,28] With time con-

49 straints, misrepresentations of inherent time delays or temporal uncertainties could lead

50 to a missed deadline and consequently an indecision.

51 Building on our past work,[8] we developed a high pressure task with a time constraint

52 to examine how humans select decision times. We tested the idea that humans opti-

53 mally account for time delays and temporal uncertainties to select a decision time that

54 maximizes reward. Alternatively, humans may suboptimally represent time delays and

55 temporal uncertainties, which can lead to an excessive number of indecisions. In **Exper-**

56 **iment 1**, we found humans were suboptimal and observed excessive indecisions that

57 led to a below chance win rate. Computational modelling work suggested that subopti-

58 mality arose by failing to account for the time delay and temporal uncertainty associated

59 with switching from reacting to guessing. **Experiment 2** showed for the first time, to

60 our knowledge, the existence of an additional time delay and uncertainty when switch-

61 ing from reacting to guessing within a trial. Taken together, our work suggests that

62 humans suboptimally represent the time delay and temporal uncertainty associated with

63 switching from reacting to guessing, leading to indecisive behaviour.

64 ## RESULTS

65 ## Experiment 1

66 **Experimental Design.**

67 The goal of **Experiment 1** was to test how stimulus timing influenced indecisive be-

68 haviour. Briefly, participants began each trial by moving their cursor into a start position

69 (**Fig. 1A**).

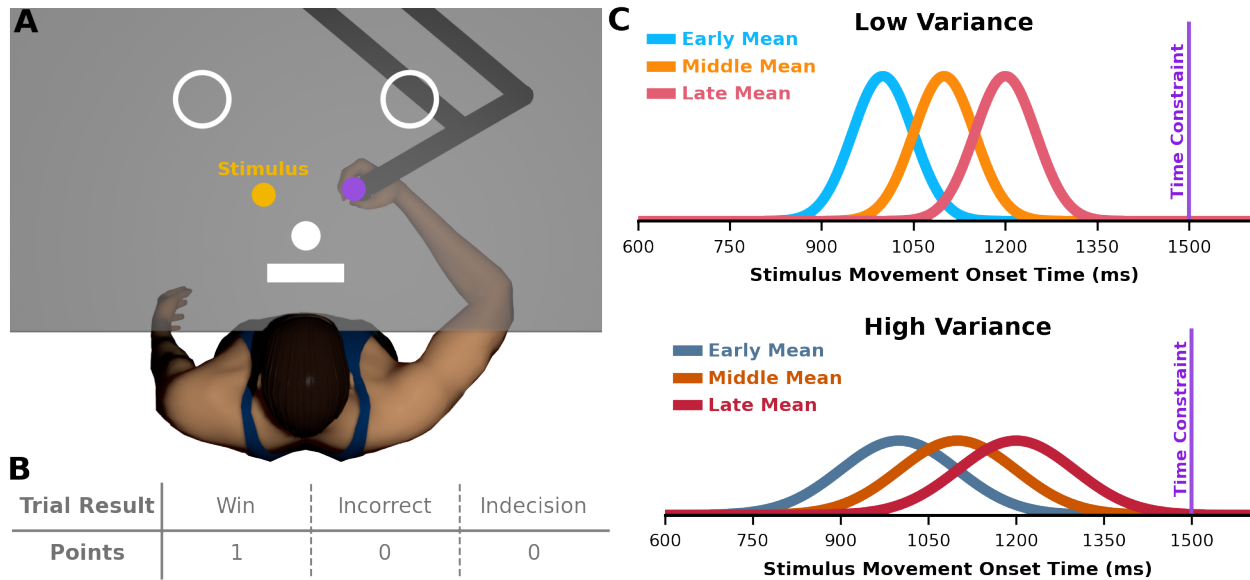**Figure 1: Experimental Design. A)** Participants grasped the handle of a robotic manipulandum and made reaching movements in the horizontal plane. An LCD projected images (start position, targets) onto a semi-silvered mirror. Participants began each trial by moving their cursor (purple) into the start position (solid white circle). At the start of the trial (0 ms), they heard a tone and saw two targets (white rings) and a timing bar (white rectangle) appear on the screen. During each trial, a stimulus (yellow cursor) would move quickly in a straight line to one of the two targets. Participants were instructed to reach the same target as the stimulus within a time constraint of 1500 ms. This time constraint was visually represented with a timing bar (white rectangle) that decreased in width according to the elapsed time. **B)** A trial was considered a win and the participant received one point if they successfully reached the same target as the stimulus within the time constraint. A trial was considered incorrect and the participant received zero points if they reached the opposite target as the stimulus within the time constraint. A trial was considered an indecision and the participant received 0 points if they failed to reach a target within the time constraint. **C)** Stimulus movement onset on each trial was randomly drawn from a specific probability distribution in each condition. Using a within experimental design, we manipulated the mean (early, middle, late) and standard deviation (low, high) of the stimulus movement onset probability distribution. For the main manuscript we focus on results for the low variance conditions, with high variance conditions results shown in **Supplementary A.**

70   The stimulus, represented as a cursor on the screen, would quickly move to one of the

71   two target circles. Participants were instructed to reach the same target as the stimulus

72   within a time constraint of 1500 ms. The time remaining in each trial was represented

73   visually with a timing bar that decreased in width according to the elapsed time. Thus,

74   participants were fully aware of how much time they had left relative to the time con-

75   straint. A trial was considered a win and the participant received one point if they suc-

76   cessfully reached the same target as the stimulus within the time constraint (**Fig. 1B**).

77   A trial was considered incorrect and the participant received zero points if they reached

78 the opposite target as the stimulus within the time constraint. A trial was considered an

79 indecision and the participant received zero points if they failed to reach a target within

80 the time constraint.

81   For each trial within a condition, the stimulus movement onset was drawn from the

82 same normal distribution. Using a 3 x 2 within experimental design (**Fig. 1C**), in sepa-

83 rate blocks we manipulated the stimulus movement onset mean (early mean = 1000 ms,

84 middle mean = 1100 ms, late mean = 1200 ms) and standard deviation (low variance =

85 50 ms, high variance = 150 ms). For the purposes of the main manuscript we focus on

86 the results of the low variance conditions, but report the findings for the high variance

87 conditions in **Supplementary A**.

Participant timing behaviour.

89 Participant movement onset for the low variance conditions is shown in **Fig. 2A**. We

90 found a significant main effect of stimulus movement onset mean ($F[1.55,29.48] = 4.36$,

91 $p = 0.030$) and variance ($F[1.00,19.00]$, $p = 0.017$). There was no significant interaction

92 between stimulus movement onset mean and variance ($F[1.66,31.47]$, $p = 0.565$). When

93 collapsed across low and high variance, participant movement onsets were significantly

94 greater in the *middle mean* conditions compared to the *early mean* conditions ($p = 0.014$,

95 $\hat{\theta} = 72.5\%$), suggesting that participants waited longer to react to the stimulus movement

96 and guessed later in time. Again, when collapsed across low and high variance, partic-

97 ipant movement onset significantly decreased from the *middle mean* conditions to the

98 *late mean* conditions ($p = 0.018$, $\hat{\theta} = 62.5\%$). Here, an earlier participant movement on-

99 set in the *late mean* condition suggests that participants attempted to wait and react to

100 the stimulus, but ended up guessing.

101   Participant movement onset standard deviation for the low variance conditions is

102 shown in **Fig. 2B**. There was a main effect of mean ($F[1.38, 26.28]$, $p = 0.018$) and

103 variance ($F[1.00,19.00]$, $p < 0.001$) of the stimulus movement onset, and no significant

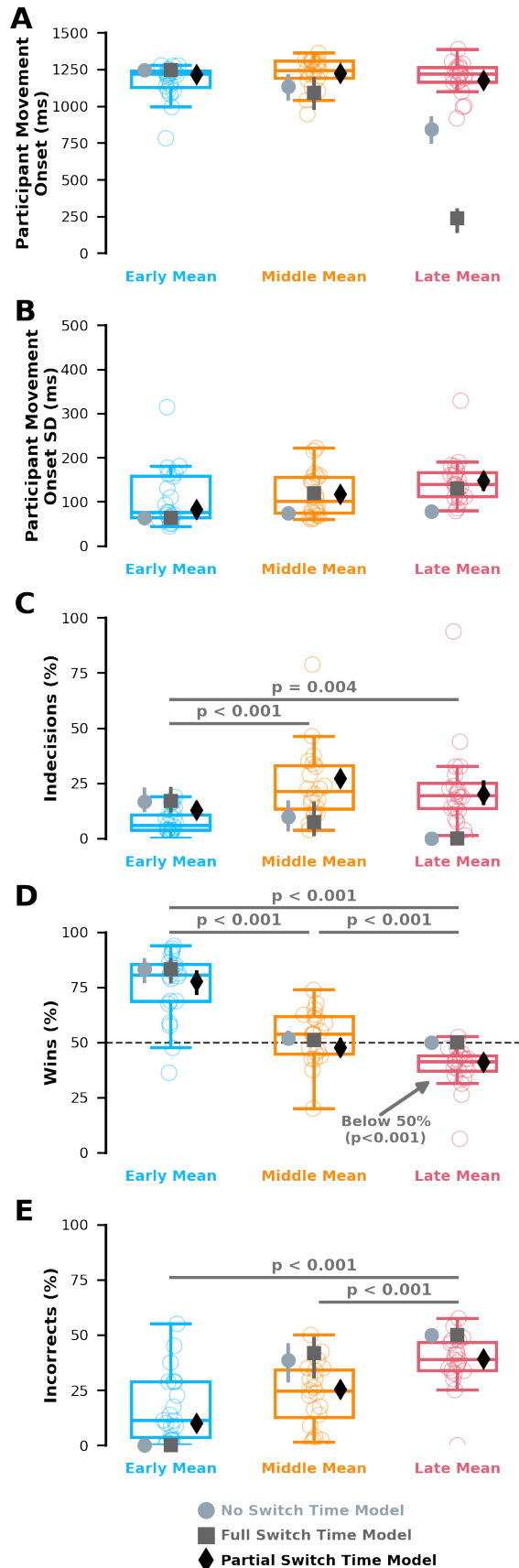104 interaction ($F[1.98, 37.58]$, $p = 0.097$).

Figure 2: Behaviour Results. **A)** Participant movement onset, **B)** participant movement onset standard deviation, **C)** indecisions, **D)** wins, and **E)** incorrects are shown for each condition. In our high time pressure task, participants made a high proportion of indecisions. Open circles are individual participant data. Filled icons are the predicted behavior of the three models, see legend for detail. Interestingly, we also found that the average win percentage (41.25%) was significantly below the 50% chance level ($p < 0.001$) in the *late mean* condition, clearly demonstrating suboptimal behaviour. Critically, participants would have earned more points if they had simply guessed earlier on all trials, rather than attempting to react to the stimulus. **Model Results**: Only the Partial Switch Time Model, which had only a partial representation of the time delay and uncertainty when switching from reacting to guessing, was able to predict the indecisions and a suboptimal win rate (below 50%) in the *late mean* condition. See **Fig. 3** for the time varying model predictions for the *late mean* condition. Collectively, our findings show that humans are suboptimal and excessively indecisive.

105   When collapsed across variance, waiting to react and then guessing in the *late mean*

106   conditions led to a higher standard deviation of participant movement onset relative to

107   the *middle mean* (p = 0.039, $\hat{\theta}$ = 70.0%) and *early mean* (p < 0.001, $\hat{\theta}$ = 77.5%) conditions.

108   **Participants are suboptimal and excessively indecisive.**

109   We calculated the indecisions (**Fig. 2C**), wins (**Fig. 2D**), and incorrect decisions (**Fig. 2E**)

110   for each of the experimental conditions. Participants displayed a substantial number of

111   indecisions. The median percentage of indecisions was 15.0% [range: 0.0 - 93.8%] across

112   all conditions, with the *late mean* condition having a median percentage of indecisions

113   of 19.4% [range: 1.2%, 93.8%]. We found a significant interaction between stimulus

114   movement onset and variance for indecisions (F[1.57, 28.78] = 5.58, p = 0.013). In low

115   variance conditions, participants made significantly more indecisions in the *middle mean*

116   condition than the *early mean* condition (p<0.001, $\hat{\theta}$ = 85.0%; **Fig. 2C**). Additionally,

117   participants made significantly more indecisions in the *late mean* condition compared to

118   the *early mean* condition (p<0.004, $\hat{\theta}$ = 80.0%).

119   The win percentage across all conditions was 56.25% (range: 6.2%, 93.8%; **Fig. 2D**).

120   We found a significant interaction between stimulus movement onset mean and variance

121   for wins (F[1.54, 29.30] = 23.73, p<0.001). The *late mean* condition had significantly less

122   wins than the *early mean* condition (p < 0.001, $\hat{\theta}$ = 95.0%). Interestingly, in the *late mean*

123   condition we found that the average win percentage was significantly below the 50%

124   chance level (p<0.001; $\hat{\theta}$ = 95.0%), which was true for 19 out of 20 participants. Since

125   guessing on every trial would lead to a win percentage of 50%, the only way participants

126   would be below chance is if they were excessively indecisive. The incorrect percentage

127   across all conditions was 26.3% [range: 0.0%, 57.5%; **Fig. 2E**]. We found significant in-

128   teractions between stimulus movement onset mean and variance for incorrect decisions

129   (F[1.66,31.51] = 3.72, p = 0.033). Participants displayed a greater percentage of incor-

130   rect decisions in the *late mean* condition than the *early mean* condition (p < 0.001, $\hat{\theta}$ =

131   92.5%).

Decision-Making Models

In our task, participants must make a decision of whether to react to the stimulus or guess. For **Experiment 1**, we tested three different models: i) No Switch Time Model, ii) Full Switch Time Model and iii) Partial Switch Time Model (**Fig. 3**, left column). The decision policy of all models considers the expected value ($\mathbb{E}[R|\tau]$) to determine the time (τ) to transition from reacting to guessing. Expected value is defined as

$$
\begin{aligned}
\mathbb{E}[R|\tau] =\ & P(Win|\tau) \cdot R_{Win} \\
& + P(Incorrect|\tau) \cdot R_{Incorrect} \\
& + P(Indecision|\tau) \cdot R_{Indecision},
\end{aligned}
\tag{1}
$$

where $P(Win|\tau)$ is the probability of a win, $P(Incorrect|\tau)$ is the probability of an incorrect, and $P(Indecision|\tau)$ is the probability of an indecision. $R_{Win} = 1$, $R_{Incorrect} = 0$, and $R_{Indecision} = 0$ correspond to the reward structure of the task (**Fig. 1B**). The decision policy of each model maximized expected reward to determine the optimal time to transition from reacting to guessing (τ^*) according to

$$
\tau^* = \underset{\tau}{argmax}[\mathbb{E}(R|\tau)].
\tag{2}
$$

Each model has varying knowledge of the different parameters (**Fig. 3**, left column). A model can have full knowledge or partial knowledge of a particular parameter. With full knowledge, the decision policy fully utilizes the parameter when selecting the time to transition from reacting to guessing. With partial knowledge, the decision policy utilizes its partial and imperfect representation of the parameter. Here the idea is that a human may have an imperfect representation of some parameter when determining a transition time, even though that particular parameter will still influence behaviour. As an example, one could plan for only some portion of a time delay, but then end up deciding too late because they did not fully account for the entire time delay. All model parameter values are described in **Supplementary B**.
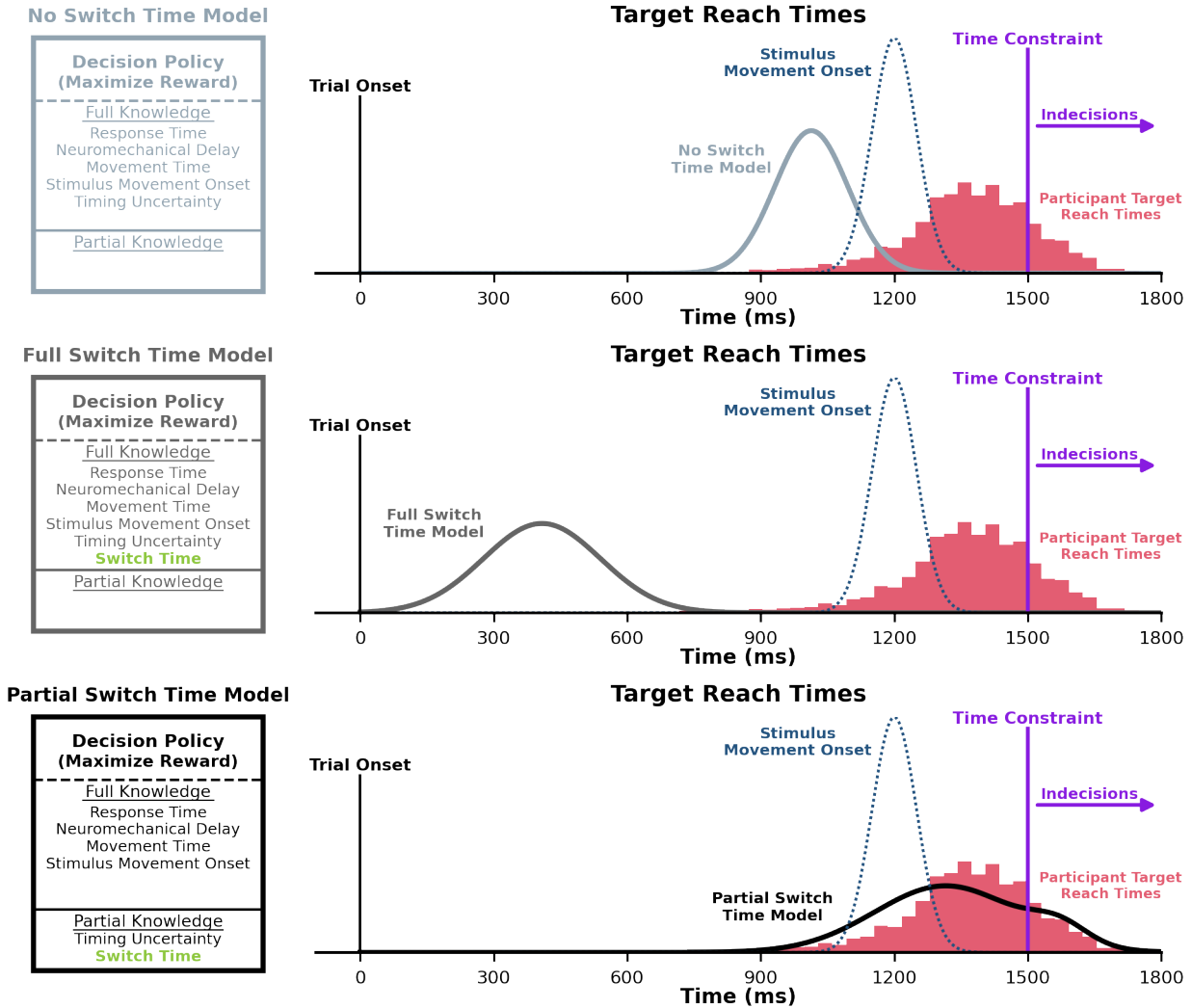
Figure 3: Models. No Switch Time Model (**top row**, light grey), Full Switch Time Model (**middle row**, dark grey), and Partial Switch Time Model (**bottom row**, black). Each decision policy maximizes reward to select a time to transition from reacting to guessing. The decision policy of each model has different knowledge, full or partial, of the delays and uncertainties associated with the various parameters (e.g., response time, switch time). **Top Row)** The No Switch Time Model (light grey) has full knowledge of all its model parameters. However, it does not include the potential delay and uncertainty when switching from reaching to guessing, which we term 'switch time'. **Middle Row**) The Full Switch Time Model (dark gray) has knowledge of all model parameters, including switch time (bright green). **Bottom Row)** Finally, the Partial Switch Time Model (black) has knowledge of several of the model parameters, but is only partially aware of the stopping time uncertainty and the switch time (delay and uncertainty). Only the Partial Switch Time Model is able to capture the participant target reach times (pink) in the *late mean* condition (stimulus movement onset; blue), allowing it to explain indecisions (**Fig. 2C**) and suboptimal win rates (**Fig. 2D**).

No Switch Time Model

153

154 We first considered a model that incorporated various time delays and temporal uncer-

155 tainties from sources previously identified in the literature: response time, neuromechan-

156 ical delay, movement time, stimulus movement onset, and timing uncertainty. Note,

157 unlike the other models we will address below, this model did not consider a 'switch

158 time' delay and uncertainty because it was not considered in past literature. Hence, we

159 termed it the No Switch Time Model.

160   In the *late mean* condition, the No Switch Time Model underestimated participant

161 movement onset (**Fig. 2A**), underestimated indecisions (**Fig. 2C**), and overestimated

162 wins (**Fig. 2D**). During this condition, participants displayed 19% indecisions on average

163 and a win percentage significantly below chance. One reason that the No Switch Time

164 Model was unable to capture behaviour is because it did not consider the potential

165 delays and uncertainties that might exist when switching from reacting to guessing.

166 *Full Switch Time Model*

167 Next we considered a model that additionally incorporated the potential existence of

168 a switch time delay and uncertainty when transitioning from reacting to guessing. For

169 this Full Switch Time Model, we assumed that the model had full knowledge of the time

170 delay and uncertainty when switching from reacting to guessing.

171   Yet, despite including switch time, the Full Switch Time Model also performed poorly

172 in the *late mean* condition by under-predicting participant movement onset (**Fig. 2A**),

173 being unable to predict indecisions (**Fig. 2C**), and not being able to predict less than

174 50% wins (**Fig. 2D**). An explanation for why this model did not do well to explain indeci-

175 sions is that humans may not have full knowledge of this potential switch time delay and

176 uncertainty.

177 *Partial Switch Time Model*

178 Finally, we considered a model that had only partial knowledge of a potential switch time

179 delay and uncertainty when transitioning from reaching to guessing. That is, this model

180 specifically tests whether humans have an imperfect representation of a switch time delay

181 and uncertainty. The model also had partial knowledge of timing uncertainty, which the

182 fitting procedure found to further improve model fits. The Partial Switch Time Model

183 was able to replicate all aspects of behaviour (**Fig. 2**). Crucially, it was able to capture

184 suboptimal behaviour in the *late mean* condition, where we found that an excessive

185 percentage of indecisions (**Fig. 2C**, **Fig. 3**) led to a lower than chance win percentage

186 (**Fig. 2D**).

Experiment 2

188 Our behavioural findings in **Experiment 1** demonstrated that participants were sub-

189 optimal decision makers. Through our modelling efforts, we were able to capture this

190 suboptimal decision-making by including a switch time delay and uncertainty when tran-

191 sitioning from reacting to guessing. The switch time delay and uncertainty were only

192 partially represented by the Partial Switch Time Model when determining the optimal

193 time to switch from reacting and guessing. However, we are not aware of any work that

194 considers a delay and uncertainty associated with switching from reacting to guessing

195 within a trial. The goal of **Experiment 2** was to determine if there is indeed a switch

196 delay and uncertainty that occurs when humans transition from reacting to guessing.

Experimental Design

198 For all conditions, participants controlled a visible cursor that was aligned with their hand

199 position. They started each trial by moving their cursor into a start position. Trial onset

200 began with the appearance of both the stimulus (yellow cursor) and two targets. Par-

201 ticipants could experience two trial types: react trials or guess trials. In the react trials,

202 participants saw the stimulus move and were instructed to as quickly as possible follow

203 the stimulus to one of the targets (**Fig. 4A**). In the guess trials, participants saw the stim-

204 ulus disappear from the start circle. They were instructed to guess one of the two targets

205 as quickly as possible (**Fig. 4B**). Following trial onset, the movement or disappearance

206 of the stimulus was drawn from a normal distribution with a mean of 800ms and a stan-

207 dard deviation of 50ms. There were three experimental conditions (**Fig. 4C**): the *react*

208 *or guess* condition, the *only react* condition, and the *only guess* condition.
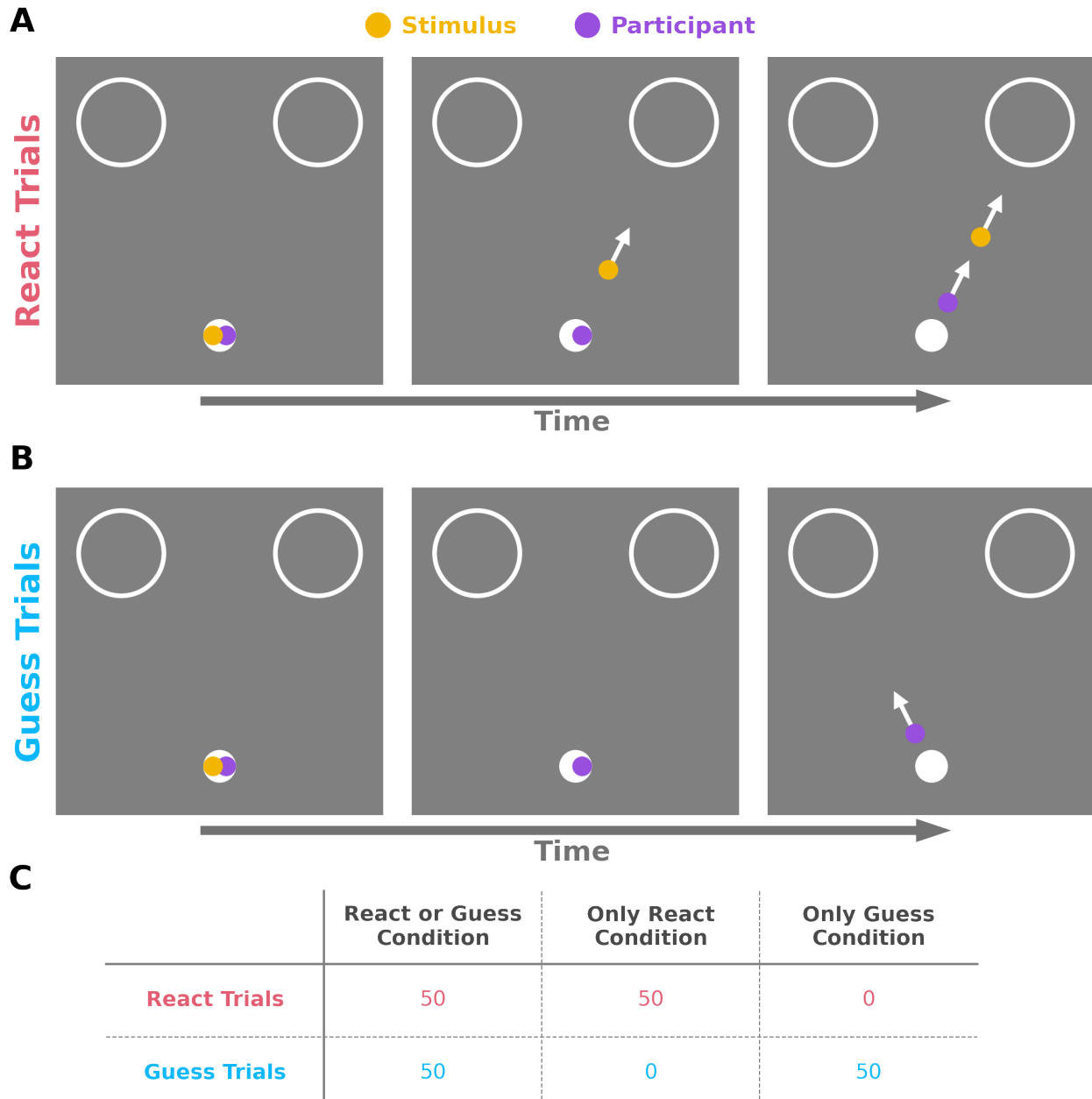
Figure 4: Experiment 2 Design. The goal of this experiment was to test the idea that there is a delay and uncertainty associated with switching from reacting to guessing, as suggested by our findings in Experiment 1. **A)** Participants responded to two different types of stimuli. In the react trials (pink), the stimulus (yellow cursor) would move to one of the two potential targets. Participants were instructed to reach the same target as the stimulus as quickly as possible. **B)** In the guess trials (blue), the stimulus disappeared from the start position. Once the stimulus disappeared, participants were instructed to guess which target the stimulus would appear in and select that target as quickly as possible. After the participant reached the target, the stimulus cursor would appear in one of the targets. **C)** We had three experimental conditions. In the *react or guess* condition, react trials and guess trials were randomly interleaved (50 react trials and 50 guess trials). Participants were informed that the stimulus would either move to one of the targets or disappear. In the *only react* condition, participants were informed that the stimulus would alway move to one of the two targets (50 react trials and 0 guess trials). They were also told that the stimulus would not disappear. In the *only guess* condition, participants were informed that the stimulus would always disappear (0 react trials and 50 guess trials). They were also informed the stimulus would not move.

209 In the *react or guess* condition, react trials and guess trials were randomly interleaved (50

210 react trials and 50 guess trials). Participants were informed that the stimulus would either

211 move to one of the targets or disappear. In the *only react* condition, participants were

212 informed that the stimulus would always move to one of the two targets (50 react trials

213 and 0 guess trials). They were also told that the stimulus would not disappear. In the *only*

214 *guess* condition, participants were informed that the stimulus would always disappear (0

215 react trials and 50 guess trials). They were also informed that it would not move to one

216 of the two targets.

217 During the *react or guess* condition, we reasoned that participants would prefer to

218 react because they would be guaranteed to select the correct target. As a result, in

219 the *react or guess* condition, if the stimulus disappeared the participant would switch

220 from reacting to guessing when selecting a target. Conversely, during the *only guess*

221 condition, if the stimulus disappeared participants would not have to switch from reacting

222 to guessing. Thus, if there is a delay when switching from reacting to guessing, we

223 would expect a greater response time for the guess trials in the *react or guess* condition

224 compared to the guess trials in the guess only condition.

225 **Response Time**

226 Average participant response times are shown for react and guess trials for each condi-

227 tion are shown in **Fig. 5A**. As expected, we found significantly greater response times for

228 guess trials in the *react or guess* condition when compared to the *only guess* condition

229 ($p < 0.001$, $\hat{\theta} = 100.0\%$), which was displayed by all participants. These comparatively

230 greater response times for guess trials in the *react or guess* condition supports the idea

231 that there is a switch time delay when transitioning from reacting to guessing.
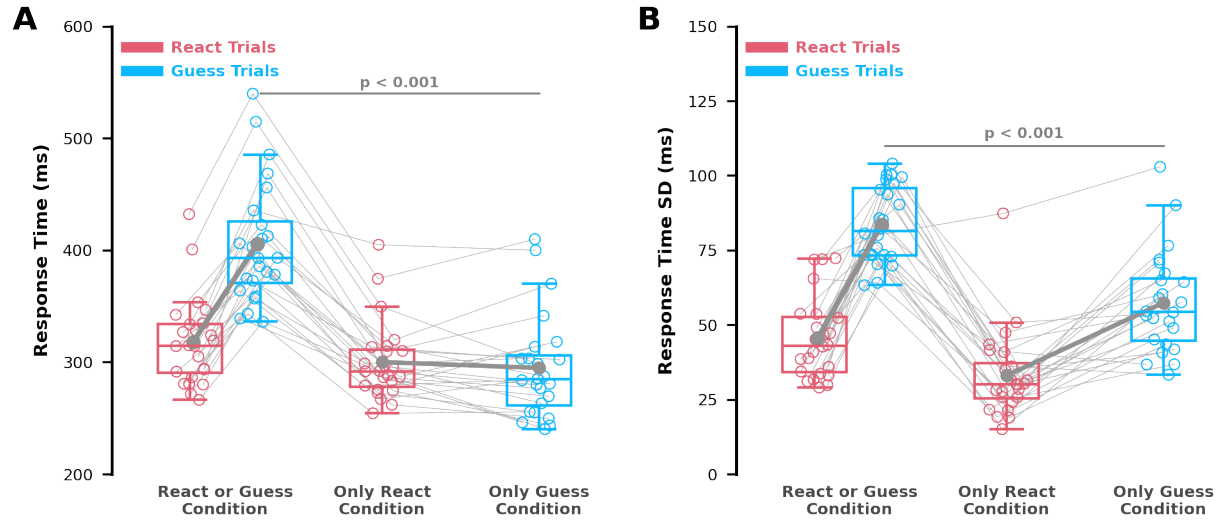
Figure 5: Response Times. A) Response time (y-axis) for each of the experimental conditions (x-axis). Participants had significantly greater response times for guess trials in the *react or guess* condition compared to the *only guess* condition. Critically, this result suggests there is an additional delay when participants initially wait to react to the stimulus and then switch to guessing. **B)** Standard deviation of response times (y-axis) was used to quantify participant response time uncertainty for each of the experimental conditions (x-axis). Participants had significantly greater response time uncertainty for guess trials in the *react or guess* condition than in the *only guess* condition. Similarly, this finding suggests there is additional uncertainty when participants initially wait to react to the stimulus and then switch to guessing. These results provide empirical evidence for an additional time delay and temporal uncertainty when switching from reacting to guessing.

Likewise, if there was a switch time delay we would also expect a comparatively greater response time difference between guess and react trials in the *react or guess* condition, compared to the response time difference between *only guess* trials and *only react* trials [i.e., guess - react (*react or guess* condition) > guess - react (guess only and react only conditions)]. Indeed, we found a greater response time difference between guess and react trials in the *react or guess* condition, compared to the response time difference between the guess only and react only conditions (p < 0.001, $\hat{\theta}$ = 66.7%; **Fig. 5A**). This result shows that the response time differences between guess and react trials are not due to dual tasking[29] or task switching between trials,[30,31,32] which would not show this relative difference [i.e., guess - react (*react or guess* condition) = guess - react (guess only and react only conditions)].

13

Response Time Uncertainty

We also examined participant response time uncertainty, calculated as the standard deviation (**Fig. 5B**). Response time uncertainty on guess trials was significantly greater in the *react or guess* condition compared to the *only guess* condition (p < 0.001). This result suggests that there is additional uncertainty when participants switch from reacting to guessing.

Discussion

Participants were suboptimal decision-makers and excessively indecisive in a high time pressure task. Computational modelling suggested that excessive indecisions were a result of failing to account for a delay and uncertainty associated with switching from reacting to guessing. We then showed empirical evidence of an additional delay and uncertainty when switching from reacting to guessing. Taken together, we found that participants were suboptimal decision-makers and excessively indecisive because they did not account for the time delay and temporal uncertainty when switching from reacting to guessing.

In **Experiment 1**, participants were required to reach the same target as a cursor before a time constraint. Within a trial, they could either react to a moving stimulus or guess which of the two targets would be correct. We saw that 95% of participants had a win rate less than chance (50%) in the *late mean* condition, which corresponded with an average of 19.4% indecisions. This proportion of indecisions aligns with our recent prior work that examined competitive human-human decision-making with a high time pressure.[8] In this competitive task, one participant attempted to reach the same target as their opponent, while the other tried to reach the opposite target within a time constraint. It was suggested that the high proportion of indecisions were the result of participants waiting too long to acquire sensory information of their opponent, despite the impending time deadline. Likewise, we found a high proportion of indecisions across experimental conditions. Our results would also suggest that participants waited to ac-

quire sensory information of when the stimuli would move. Moreover, building upon Lokesh and colleagues (2022), our work suggests that a key contributor leading to excessive indecisions is failing to account for the time delay and temporal uncertainty when switching from reacting to guessing.

Past work has suggested that humans can nearly optimally account for time delays and temporal uncertainty when performing decision-making[15,33,34] and movement tasks[16,35] when attempting to maximize reward. Here we considered two optimal models, the No Switch Time Model and Full Switch Time Model, which both had full knowledge of all available time delays and temporal uncertainties. Interestingly, both the No Switch Time Model and Full Switch Time Model showed that even when fully accounting for all sensorimotor delays and uncertainties, indecisions were a part of an optimal strategy in all but one of the six conditions. In other words, given the inherent delays and uncertainty of our nervous system,[20] an optimal strategy of earning maximal reward may involve indecisive behaviour on some proportion of trials. We are unaware of any work in the literature suggesting that some level of indecisions may be optimal. Even though making some indecisions can be optimal, our results in **Experiment 1** were in support of the idea that humans are suboptimal. Specifically, in the *late mean* condition, we found that humans were suboptimal since they had a win percentage lower than chance, which arose from an excessive number of indecisions. The Partial Switch Time Model was suboptimal, since it had a partial representation of the time delay and temporal uncertainties associated with switching from reacting to guessing. We found that this model best explained behaviour, including a below chance win percentage and an excessive number of indecisions. The Partial Switch Time Model supports the notion that humans suboptimally select decision times when under high time pressures. An interesting future direction would be to test whether different reward structures, such as placing a higher reward on wins or punishing indecisions,[36,37,38,39] would provide a means to reduce an excessive number of indecisions.

297 The combined empirical evidence of **Experiment 1** and computational modelling

298 suggested the existence of a time delay and uncertainty when switching from reacting

299 to guessing. However, we were unaware of any work in the literature to support this

300 idea. In **Experiment 2** we tested the notion of a more delayed and uncertain response

301 time when switching from reacting to guessing, compared to guessing by itself. In-

302 deed, we found that when participants had to switch from reacting to guessing, their

303 response times were significantly slower and more uncertain than when they only had

304 to guess. One possibility for increased time delays and temporal uncertainty could be

305 related to switching between different processing 'modes'. In our task, participants may

306 have switched from a 'react mode' that corresponded to preparing to follow the stimulus,

307 to a 'guess mode' to randomly select one of the targets.

308 Dutilh and colleagues (2011) explored the idea of switching between a stimulus con-

309 trolled (i.e. react) mode and a guess mode between trials.[40] In their task, participants

310 were required to discriminate between a word stimuli from a non-word stimuli by select-

311 ing one of two buttons during a two-alternative forced choice task. Between trials, the

312 authors manipulated whether participants received more reward for accurate decisions to

313 promote reacting, or more reward for fast decisions that promoted guessing. Participants

314 displayed longer response times when transitioning from more accurate decisions to

315 fast decisions, compared to when transitioning from fast decisions to accurate decisions

316 given the same current reward weighting. The authors interpreted these results to rep-

317 resent a resistance, termed hysteresis, when switching between react and guess modes.

318 That is, participants are more likely to stay in their current mode than switch modes. They

319 also highlighted that classical decision-making models, such as drift-diffusion models[41]

320 or more recently the urgency-gating model,[42,43,44] do not consider different modes of

321 reacting or guessing. Extending upon the findings of Dutilh and colleagues (2011) that

322 examined between trial mode switching, our work suggests that humans switch react

323 and guess modes within a trial. Importantly, we find that not accounting for the time

delays and temporal uncertainties when switching from reacting to guessing gives rise to excessive indecisions. To our knowledge, it is unknown how different modes would be represented in the nervous system. One possibility is that the different modes represent different attractors from a neural dynamical systems perspective,[45,46,47,48] which would be an interesting avenue of investigation.

We found in **Experiment 2** that participant response times were more delayed by approximately 75 ms during guess trials in the *react or guess* condition, compared to guess only trials. Moreover, the response time difference between guess and react trials in the *react or guess* condition are significantly greater than the response time difference between the *guess only* and *react only* conditions. Collectively, these results suggest that participants have an initial preference to react, before having to switch to a guess. In this experiment behaviour may be explained by a strong preference to react since it yields a 100% success probability, as opposed to guessing that on average yields a 50% success probability. It would be interesting for future studies to examine if they can manipulate the magnitude or probability of reward to switch a preference between reacting or guessing, and how this impacts indecisive behaviour.

Indecisions are often not studied since many decision-making tasks do not permit a non-response or simply do not consider responses made after some time constraint. A limitation of the commonly used two-alternative forced choice task without a time constraint is that the participant or animal must select one of two potential options, which does not allow for indecisive behaviour. For decision-making tasks with a time constraint, late responses beyond the deadline are typically not included in the analysis.[10,12,13,49] Furthermore, previous modeling work on decision-making under time constraints has primarily focused on the response times and response time distributions of correct and incorrect decisions.[9,50] However, a focus on only correct and incorrect decisions leaves out a crucial and prevalent aspect of decision-making—indecisive behaviour.

Here we showed in our first experiment that humans are excessively indecisive under

351 time constraints. Computational work and a second experiment suggested that indeci-

352 sive behaviour can occur by not accounting for the time delay and temporal uncertainty

353 associated with switching from reacting to guessing. Our experimental and theoretical

354 approach offers a new paradigm to study indecisions, which has received surprisingly

355 little attention despite its ecological relevance. This work advances how indecisive be-

356 haviour arises, which is important to understand when attempting to avoid potentially

357 catastrophic events during high time pressure scenarios.

Methods

Participants

360 44 participants participated across two experiments 20 individuals participated in **Exper-**

361 **iment 1** and 24 individuals participated in **Experiment 2**. All participants reported they

362 were free from musculoskeletal injuries, neurological conditions, or sensory impairments.

363 In addition to a base compensation of $5.00, we informed them they would receive a

364 performance-based compensation of up to $5.00. Participants received the full $10.00

365 once they completed the experiment irrespective of their performance. All participants

366 provided written informed consent to participate in the experiment and the procedures

367 were approved by the University of Delaware's Institutional Review Board.

Apparatus

369 For both experiments we used an end point KINARM robot (**Fig. 1A**; BKIN Technologies,

370 Kingston, ON). Each participant was seated on an adjustable chair in front of one of the

371 end-point robots. Each participant grasped the handle of a robotic manipulandum and

372 made reaching movements in the horizontal plane. A semi-silvered mirror blocked the

373 vision of the upper limb and displayed virtual images (e.g., targets, cursors) from an LCD

374 screen. In all experiments the cursor was aligned with the position of the hand. The

375 semi-silvered mirror occluded the vision of their hand. Kinematic data were recorded at

376 1,000 Hz and stored offline for data analysis.

Experiment 1 Design

The goal of **Experiment 1** was to study the influence of stimulus onset on indecisive behaviour. To begin the task, the participant moved their cursor (white circle, 1 cm diameter) into a start position (white circle, 1 cm diameter) (**Fig. 1A**). Then a stimulus (yellow cursor, 1 cm diameter) appeared in the start position. After a random time delay (600-2400 ms drawn from a uniform distribution), the participant heard a tone that coincided with two targets (white ring, 8 cm diameter) and a timing bar appearing 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. The timing bar was 10 cm below the start position. In each trial, the stimulus would move quickly (150 ms movement time) with a bell-shaped velocity profile into one of the two targets. The stimulus selected the left and right targets randomly with equal probability. Participants were instructed to reach the same target as the stimulus. They had to select a target within the 1500 ms time constraint, relative to trial onset. The timing bar decreased in width according to elapsed time and disappeared at 1500 ms. Visual feedback of the timing bar provided participants full knowledge of the time remaining in the trial. Participants were instructed to stay inside the start position until they decided to select a target. Importantly, participants were informed that they could select one of the targets at any time during the trial. Thus, they could either wait to react to the stimulus or guess one of the targets. Once they decided which target to select, the participant rapidly moved their cursor into the selected target.

Participants were instructed that their goal was to earn as many points as possible. A trial was considered a win if they successfully reached the same target as the stimulus within the 1500 ms time constraint. A trial was considered incorrect if they reached the opposite target as the stimulus before the time constraint. A trial was considered an indecision if they failed to reach a target within the time constraint. Participants earned one point for a win, zero points for being incorrect, and zero points for making an indecision

404 (**Fig. 1B**).

405   For each trial within a condition, the stimulus movement onset was drawn from the

406 same normal distribution. Using a 3 x 2 within experimental design, we manipulated the

407 stimulus movement onset mean (*early mean* = 1000 ms, *middle mean* = 1100 ms, *late*

408 *mean* = 1200 ms) and standard deviation (low variance = 50 ms, high variance = 150

409 ms) that resulted in 6 experimental conditions (**Fig. 1C**). Each condition was performed

410 separately using a block design.

411   Participants completed 605 total trials. They first performed 25 baseline trials, as well

412 as 80 trials per experimental condition that were each separated by 25 washout trials.

413 The stimulus movement onset during baseline and washout trials was randomly drawn

414 from a discrete uniform distribution [400, 437.5,…,1300 ms]. The washout condition was

415 designed to minimize the influence of the stimulus movement onset distribution of the

416 previous condition. Condition order was randomized across participants.

417   Prior to **Experiment 1**, participants performed two separate tasks to estimate re-

418 sponse time (response time task; **Supplementary D**) and timing uncertainty (timing un-

419 certainty task; **Supplementary E**). We counterbalanced the order of the response time

420 and timing uncertainty tasks.

Experiment 2 Design

422 The goal of **Experiment 2** was to test whether there is a time delay and uncertainty

423 when switching from reacting to guessing. To investigate, participants began each trial

424 by moving their cursor into a start position. Then, a stimulus cursor appeared in the start

425 position. Each trial began with a beep and the two potential targets appeared on the

426 screen. Here participants experienced two different types of trials: react trials or guess

427 trials. The react trials consisted of the stimulus moving to one of the two targets (**Fig. 4A**).

428 Participants were instructed to follow the stimulus as quickly as possible. The guess trials

429 consisted of the stimulus disappearing from the start position (**Fig. 4B**). Participants were

430 instructed to select the target they believed the stimulus would end up in as quickly as

431 possible. After the participant selected their target, the stimulus cursor appeared in one

432 of the two targets. The stimulus movement onset (reaction trials) or disappearance time

433 (guess trials) was drawn from a normal distribution (mean = 800 ms, standard deviation =

434 50 ms). The stimulus randomly selected the left and right targets with equal probability.

435   Using these react and guess trials, participants performed a within experimental de-

436 sign with three conditions: *react or guess* condition, *only react* condition, and *only guess*

437 condition. In the *react or guess* condition, we pseudorandomly interleaved the 50 react

438 trials and 50 guess trials. Participants were informed the stimulus would either move

439 to one of the targets (react trials) or disappear (guess trials). The *only react* condition

440 consisted of 50 react trials. Participants were informed that the stimulus would move to

441 one of the two targets and would not disappear. The *only guess* condition consisted of

442 50 guess trials. Participants were informed that the stimulus would only disappear and

443 would not move to one of the two targets. The *react or guess* condition was performed

444 first by participants to avoid any potential carry-over effects of repeatedly performing

445 *react or guess* trials in the other two conditions. After the *react or guess* condition, the

446 order of the *only react* condition and *only guess* condition was counterbalanced.

Data Analysis

448 Kinematics were filtered using a dual-pass, low pass, second order Butterworth filter with

449 a cutoff frequency of 14 Hz.

Experiment 1

451 *Participant movement onset*: On each trial, we found when the time point where the

452 participant hand velocity exceeded 0.05 m/s.[51,52] The mean time point across all trials

453 within a condition was used to estimate participant movement onset.

454 *Participant movement onset standard deviation*: Using all trials in a condition, we used

455 the time point where the participant hand velocity exceeded 0.05 m/s to calculate the

456 standard deviation of participant movement onsets for each condition.

457 *Outcome metrics*: Win (%): A trial was a win if participants reached the same target as

458 the stimulus before the time constraint. Incorrect (%): A trial was an incorrect if partici-

459 pants reached the opposite target as the stimulus before the time constraint. Indecision

460 (%): A trial was an indecision if participants failed to reach either target before the time

461 constraint. We calculated each of the outcome metrics as a percentage of the total trials.

462 **Experiment 2**

463 *Response time*: Response times were calculated as the difference between participant

464 movement onset and either the stimulus movement onset or stimulus disappearance

465 time. The mean time difference across all trials within a condition was used to estimate

466 the participant response times. Note that any response times greater than 650 ms or

467 less than 150 ms were removed from analysis (3.7% of trials). We calculated response

468 time separately for react and guess trials.

469 *Response time standard deviation*: We calculated the standard deviation of participant's

470 response times separately for react and guess trials.

471 **Statistics**

472 **Experiment 1 and 2**

473 We used analysis of variance (ANOVA) as omnibus tests to determine whether there

474 were main effects and interactions. We report the Greenhouse-Geiser adjusted p-values

475 and degrees of freedom. In **Experiment 1** we used a 3 (mean: early, middle, late) x

476 2 (variance: low, high) repeated measures ANOVA for each dependent variable. In **Ex-**

477 **periment 2** we used a 2 (condition: interleaved react and guess, *react or guess* only)

478 x 2 (trial type: react trials, guess trials) repeated measures ANOVA for each dependent

479 variable. For both **Experiment 1** and **2**, we performed mean comparisons using non-

480 parametric bootstrap hypothesis tests (n = 1,000,000).[53,54,55] Mean comparisons were

481 Holm-Bonferonni correct to account for multiple comparisons. Significance threshold

482 was set at α = 0.05). We also report the common-language effect size ($\hat{\theta}$).

References

1. Zacksenhouse, M., Bogacz, R., & Holmes, P. (2010). Robust versus Optimal Strategies for Two-Alternative Forced Choice Tasks. *Journal of Mathematical Psychology*, 54 (2), 230–246.

2. Bogacz, R., Brown, E., Moehlis, J., Holmes, P., & Cohen, J. D. (2006). The Physics of Optimal Decision Making: A Formal Analysis of Models of Performance in Two-Alternative Forced-Choice Tasks. *Psychological Review*, 113 (4), 700–765.

3. Cho, R. Y., Nystrom, L. E., Brown, E. T., Jones, A. D., Braver, T. S., Holmes, P. J., & Cohen, J. D. (2002). Mechanisms Underlying Dependencies of Performance on Stimulus History in a Two-Alternative Forced-Choice Task. *Cognitive, Affective, & Behavioral Neuroscience*, 2 (4), 283–299.

4. Jogan, M., & Stocker, A. A. (2014). A New Two-Alternative Forced Choice Method for the Unbiased Characterization of Perceptual Bias and Discriminability. *Journal of Vision*, 14 (3), 20–20.

5. Ratcliff, R., & Mckoon, G. (2008). The Diffusion Decision Model: Theory and Data for Two-Choice Decision Tasks. *Neural Computation*, 20 , 873–922.

6. Ulrich, R., & Miller, J. (2004). Threshold Estimation in Two-Alternative Forced-Choice (2AFC) Tasks: The Spearman-Kärber Method. *Perception & Psychophysics*, 66 (3), 517–533.

7. Tyler, C. W., & Chen, C.-C. (2000). Signal Detection Theory in the 2AFC Paradigm: Attention, Channel Uncertainty and Probability Summation. *Vision Research*, 40 (22), 3121–3144.

8. Lokesh, R., Sullivan, S., Calalo, J. A., Roth, A., Swanik, B., Carter, M. J., & Cashaback, J. G. A. (2022). Humans Utilize Sensory Evidence of Others' Intended Action to Make Online Decisions. *Scientific Reports*, 12 (1), 8806.

9. Karsilar, H., Simen, P., Papadakis, S., & Balci, F. (2014). Speed Accuracy Trade-off under Response Deadlines. *Frontiers in Neuroscience*, 8 ,

10. Wu, T., Dufford, A. J., Mackie, M.-A., Egan, L. J., & Fan, J. (2016). The Capacity of Cognitive Control Estimated from a Perceptual Decision Making Task. *Scientific Reports*, 6 (1), 34025.

11. Philiastides, M. G., Auksztulewicz, R., Heekeren, H. R., & Blankenburg, F. (2011). Causal Role of Dorsolateral Prefrontal Cortex in Human Perceptual Decision Making. *Current Biology*, 21 (11), 980–983.

12. Dambacher, M., & Hübner, R. (2015). Time Pressure Affects the Efficiency of Perceptual Processing in Decisions under Conflict. *Psychological Research*, 79 (1), 83–94.

13. Forstmann, B. U., Dutilh, G., Brown, S., Neumann, J., Von Cramon, D. Y., Ridderinkhof, K. R., & Wagenmakers, E.-J. (2008). Striatum and Pre-SMA Facilitate Decision-Making under Time Pressure. *Proceedings of the National Academy of Sciences*, 105 (45), 17538–17542.

14. Drugowitsch, J., Moreno-Bote, R., & Pouget, A. (2014). Optimal Decision-Making with Time-Varying Evidence Reliability. *Advances in Neural Information Processing Systems*, 1 (January), 748–756.

15. Balci, F., Freestone, D., Simen, P., Desouza, L., Cohen, J. D., & Holmes, P. (2011). Optimal Temporal Risk Assessment. *Frontiers in Integrative Neuroscience*, 5 (September), 1–15.

16. Hudson, T. E., Maloney, L. T., & Landy, M. S. (2008). Optimal Compensation for Temporal Uncertainty in Movement Planning. *PLoS Computational Biology*, 4 (7), ed. by Friston, K. J.: e1000130.

17. Trommershäuser, J., Landy, M. S., & Maloney, L. T. (2006). Humans Rapidly Estimate Expected Gain in Movement Planning. *PSYCHOLOGICAL SCIENCE*, 17 (11),

18. Drugowitsch, J., Deangelis, G. C., Angelaki, D. E., & Pouget, A. (2015). Tuning the Speed-Accuracy Trade-off to Maximize Reward Rate in Multisensory Decision-Making. *eLife*, 4 (JUNE2015),

19. Acerbi, L., Wolpert, D. M., & Vijayakumar, S. (2012). Internal Representations of Temporal Statistics and Feedback Calibrate Motor-Sensory Interval Timing. *PLoS Computational Biology*, 8 (11), ed. by Maloney, L. T.: e1002771.

20. Faisal, A. A., Selen, L. P., & Wolpert, D. M. (2008). Noise in the Nervous System. *Nature Reviews Neuroscience*, 9 (4), 292–303.

21. Körding, K. P., & Wolpert, D. M. (2006). Bayesian Decision Theory in Sensorimotor Control. *Trends in Cognitive Sciences*, 10 (7), 319–326.

22. Wolpert, D. M., & Landy, M. S. (2012). Motor Control Is Decision-Making. *Current Opinion in Neurobiology*, 22 (6), 996–1003.

23. Tanis, D., Calalo, J. A., Cashaback, J. G. A., & Kurtzer, I. L. (2023). Accuracy and Effort Costs Together Lead to Temporal Asynchrony of Multiple Motor Commands. *Journal of Neurophysiology*, 129 (1), 1–6.

24. Lokesh, R., Sullivan, S. R., St. Germain, L., Roth, A. M., Calalo, J. A., Buggeln, J., Ngo, T., Marchhart, V. R. F., Carter, M. J., & Cashaback, J. G. A. (2023). Visual Accuracy Dominates over Haptic Speed for State Estimation of a Partner during Collaborative Sensorimotor Interactions. *Journal of Neurophysiology*, 130 (1), 23–42.

25. Miletić, S., & Van Maanen, L. (2019). Caution in Decision-Making under Time Pressure Is Mediated by Timing Ability. *Cognitive Psychology*, 110 , 16–29.

26. Faisal, A. A., & Wolpert, D. M. (2009). Near Optimal Combination of Sensory and Motor Uncertainty in Time during a Naturalistic Perception-Action Task. *Journal of Neurophysiology*, 101 (4), 1901–1912.

27. Ota, K., Shinya, M., & Kudo, K. (2015). Motor Planning under Temporal Uncertainty Is Suboptimal When the Gain Function Is Asymmetric. *Frontiers in Computational Neuroscience*, 9 ,

28. Drugowitsch, J., Wyart, V., Devauchelle, A.-D., & Koechlin, E. (2016). Computational Precision of Mental Inference as Critical Source of Human Choice Suboptimality. *Neuron*, 92 (6), 1398–1411.

29. Van Selst, M., & Jolicoeur, P. (1997). Decision and Response in Dual-Task Interference. *Cognitive Psychology*, 33 (3), 266–307.

30. Monsell, S. (2003). Task Switching. *Trends in Cognitive Sciences*, 7 (3), 134–140.

31. Kiesel, A., Steinhauser, M., Wendt, M., Falkenstein, M., Jost, K., Philipp, A. M., & Koch, I. (2010). Control and Interference in Task Switching—A Review. *Psychological Bulletin*, 136 (5), 849–874.

32. Rubinstein, J. S., Meyer, D. E., & Evans, J. E. (2001). Executive Control of Cognitive Processes in Task Switching. *Journal of Experimental Psychology: Human Perception and Performance*, 27 (4), 763–797.

33. Balci, F., Freestone, D., & Gallistel, C. R. (2009). Risk Assessment in Man and Mouse. *Proceedings of the National Academy of Sciences of the United States of America*, 106 (7), 2459–2463.

34. Jazayeri, M., & Shadlen, M. N. (2010). Temporal Context Calibrates Interval Timing. *Nature Neuroscience*, 13 (8), 1020–1026.

35. Dean, M., Wu, S.-W., & Maloney, L. T. (2007). Trading off Speed and Accuracy in Rapid, Goal-Directed Movements. *Journal of Vision*, 7 (5), 10.

36. Kahneman, D., & Tversky, A. (2013). Prospect Theory: An Analysis of Decision under Risk. *Handbook of the fundamentals of financial decision making: Part I* , 99–127.

37. 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 Pro-

cesses Actively Regulate Motor Exploration along Redundant Solution Manifolds. *Proceedings of the Royal Society B: Biological Sciences*, 290 (2009), 20231475.

38. 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.

39. Galea, J. M., Mallia, E., Rothwell, J., & Diedrichsen, J. (2015). The Dissociable Effects of Punishment and Reward on Motor Learning. *Nature Neuroscience*, 18 (4), 597–602.

40. Dutilh, G., Wagenmakers, E.-J., Visser, I., & van der Maas, H. L. J. (2011). A Phase Transition Model for the Speed-Accuracy Trade-Off in Response Time Experiments. *Cognitive Science*, 35 (2), 211–250.

41. Ratcliff, R., Voskuilen, C., & Teodorescu, A. (2018). Modeling 2-Alternative Forced-Choice Tasks: Accounting for Both Magnitude and Difference Effects. *Cognitive Psychology*, 103 , 1–22.

42. Cisek, P., Puskas, G. A., & El-Murr, S. (2009). Decisions in Changing Conditions: The Urgency-Gating Model. *Journal of Neuroscience*, 29 (37), 11560–11571.

43. Derosiere, G., Thura, D., Cisek, P., & Duque, J. (2021). Trading Accuracy for Speed over the Course of a Decision. *Journal of Neurophysiology*, 126 (2), 361–372.

44. Thura, D., Beauregard-Racine, J., Fradet, C.-W., & Cisek, P. (2012). Decision Making by Urgency Gating: Theory and Experimental Support. *Journal of Neurophysiology*, 108 (11), 2912–2930.

45. Erlhagen, W., & Schöner, G. (2002). Dynamic Field Theory of Movement Preparation. *Psychological Review*, 109 (3), 545–572.

46. Wang, X.-J. (2008). Decision Making in Recurrent Neuronal Circuits. *Neuron*, 60 (2), 215–234.

47. Churchland, M. M., Cunningham, J. P., Kaufman, M. T., Foster, J. D., Nuyujukian, P., Ryu, S. I., & Shenoy, K. V. (2012). Neural Population Dynamics during Reaching. *Nature*, 487 (7405), 51–56.

48. Shenoy, K. V., Sahani, M., & Churchland, M. M. (2013). Cortical Control of Arm Movements: A Dynamical Systems Perspective. *Annual Review of Neuroscience*, 36 (1), 337–359.

49. Diederich, A. (2008). A Further Test of Sequential-Sampling Models That Account for Payoff Effects on Response Bias in Perceptual Decision Tasks. *Perception & Psychophysics*, 70 (2), 229–256.

50. Farashahi, S., Ting, C. C., Kao, C. H., Wu, S. W., & Soltani, A. (2018). Dynamic Combination of Sensory and Reward Information under Time Pressure. *PLoS Computational Biology*, 14 (3), 1–26.

51. Gribble, P. L., Mullin, L. I., Cothros, N., & Mattar, A. (2003). Role of Cocontraction in Arm Movement Accuracy. *Journal of Neurophysiology*, 89 (5), 2396–2405.

52. Calalo, J. A., Roth, A. M., Lokesh, R., Sullivan, S. R., Wong, J. D., Semrau, J. A., & Cashaback, J. G. A. (2023). The Sensorimotor System Modulates Muscular Co-Contraction Relative to Visuomotor Feedback Responses to Regulate Movement Variability. *Journal of Neurophysiology*, 129 (4), 751–766.

53. Hesterberg, T. (2011). Bootstrap. *WIREs Computational Statistics*, 3 (6), 497–526.

54. Cashaback, J. G. A., McGregor, H. R., Mohatarem, A., & Gribble, P. L. (2017). Dissociating Error-Based and Reinforcement-Based Loss Functions during Sensorimotor Learning. *PLOS Computational Biology*, 13 (7), ed. by Faisal, A. A.: e1005623.

55. 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. *PLOS Computational Biology*, 15 (3), ed. by Haith, A. M.: e1006839.

56. 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.

57. Norman, R. W., & Komi, P. V. (1979). Electromechanical Delay in Skeletal Muscle under Normal Movement Conditions. *Acta Physiologica Scandinavica*, 106 (3), 241–248.

58. Rossini, P. M., & Rossi, S. (1998). Clinical Applications of Motor Evoked Potentials. *Electroencephalography and Clinical Neurophysiology*, 106 (3), 180–194.

59. 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.

60. Milstein, D. M., & Dorris, M. C. (2007). The Influence of Expected Value on Saccadic Preparation. *The Journal of Neuroscience*, 27 (18), 4810–4818.

61. 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.

Supplementary

⁴⁸⁴ ## Supplementary A: Low and High Variance Results
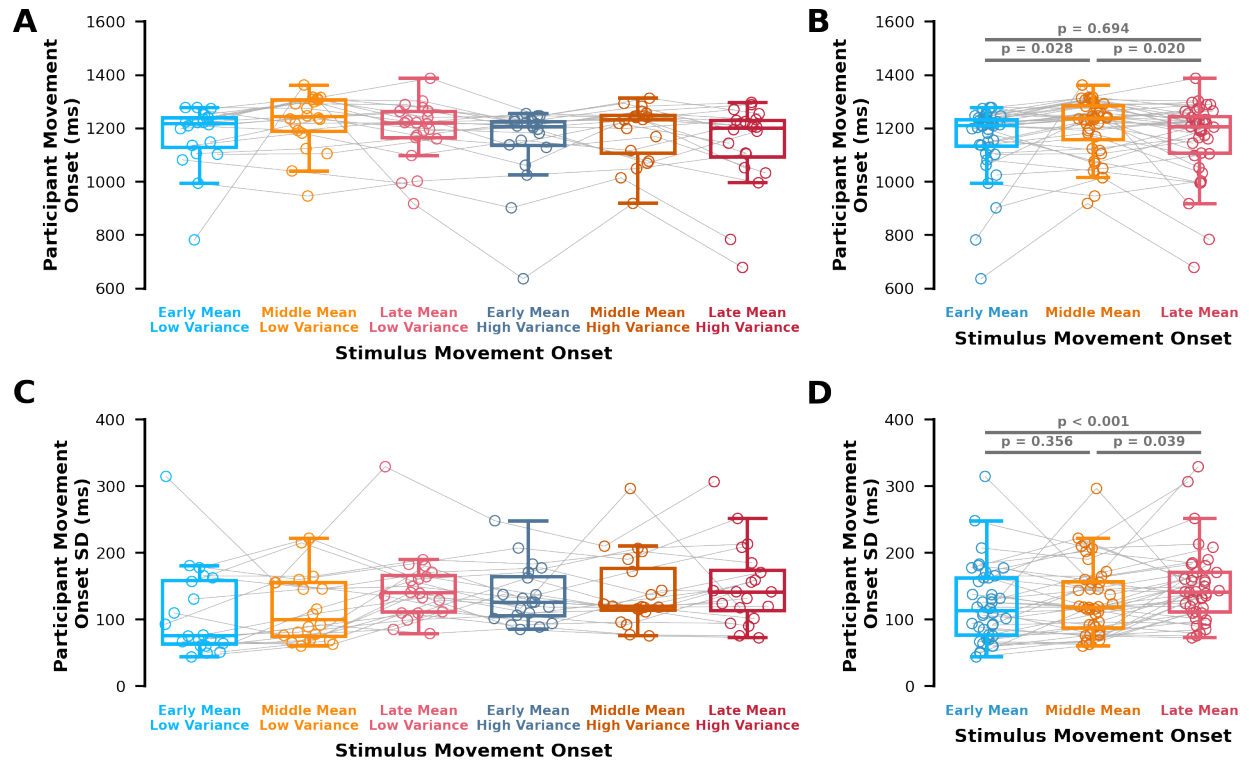
Supplementary Figure 1: Timing Behaviour. A) Average participant movement onset (y-axis) for each experimental condition (x-axis). We found a significant main effect of stimulus movement onset mean ($F[1.55,29.48] = 4.36$, $p = 0.030$) and variance ($F[1.00,19.00]$, $p = 0.017$)) on participant movement 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.
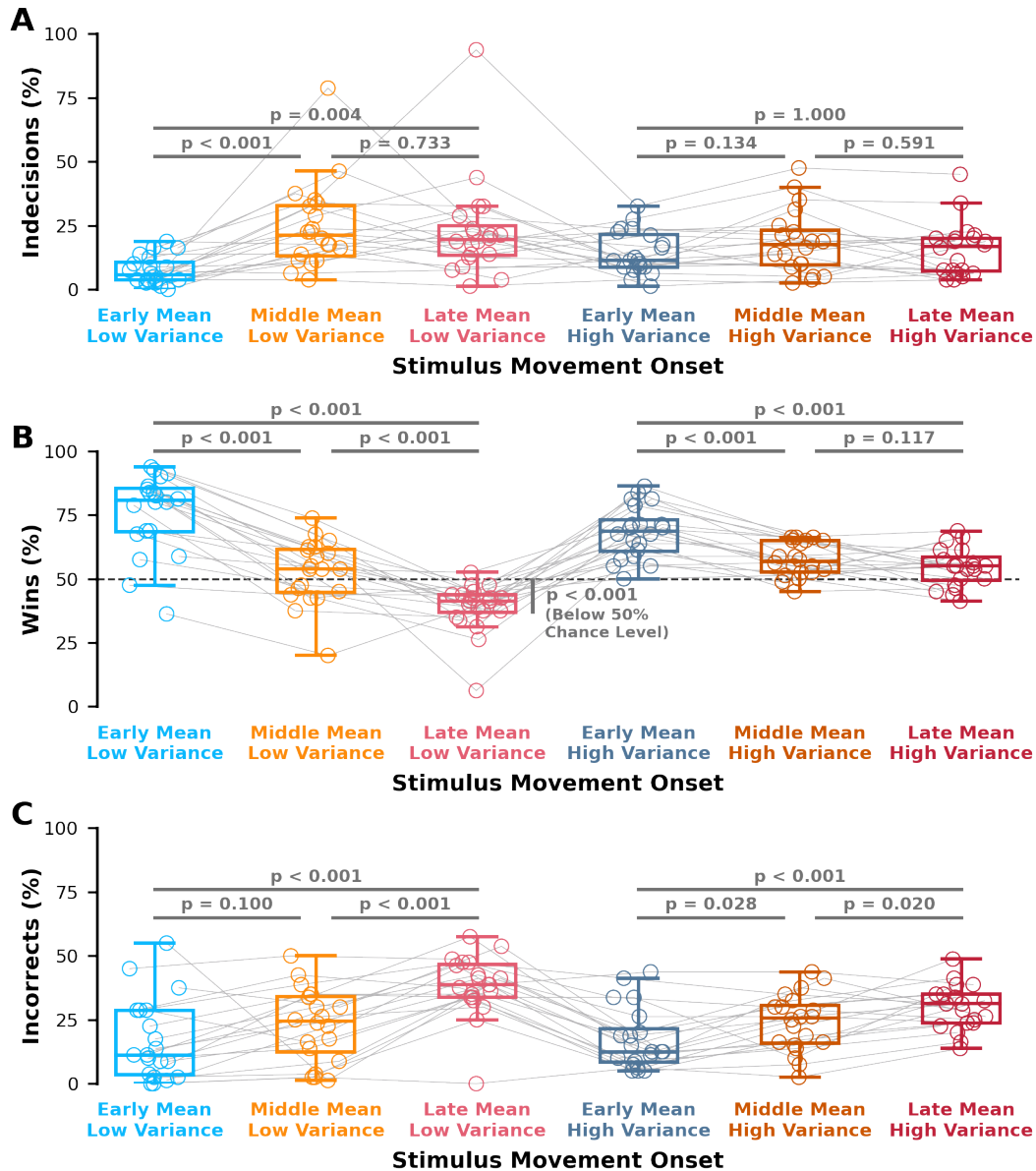
Supplementary Figure 2: Trial Outcomes. A) Indecisions (%) **B)** Wins (%), and **C)** Incorrects (%) for each condition. **A)** We found that the middle mean low variance and *late mean low variance* condition had a significantly greater number of indecisions compared to the *early mean low variance* 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: 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[56] and reach timing.[16] 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 volitional decision to move and movement onset. Movement Time represents the mean (μ_{mt}) and uncertainty (σ_{mt}) of the delay between movement onset and reaching a tar-

512 get. Stimulus Movement onset is knowledge of the mean (μ_S) and uncertainty (σ_S) of the

513 stimulus's movement onset distribution. Timing uncertainty (σ_τ) is the participant uncer-

514 tainty around the intended transition time, τ. Switch Time represents the additional delay

515 (μ_{switch}) and uncertainty (σ_{switch}) of switching from reacting to guessing. All probability

516 distributions are assumed to be normally distributed with a mean μ and standard devia-

517 tion σ. Each of our three models has a different set of known and unknown parameters.

518 A model decision policy has full knowledge of known parameters when determining the

519 optimal decision time. A model decision policy has no or partial knowledge of unknown

520 parameters when determining the optimal decision time.

521 *No Switch Time Model*

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

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

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

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

526 time mean and uncertainty in neither the known nor the unknown parameter sets. The

527 No Switch Time Model reflects the hypothesis that there is no additional delay and un-

528 certainty when switching from reacting to guessing.

529 *Full Switch Time Model*

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

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

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

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

534 Model reflects the hypothesis that participants fully account for a delay and uncertainty

535 associated with switching from reacting to guessing.

536 *Partial Switch Time Model*

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

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

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

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

541 Partial Switch Time Model reflects our hypothesis that participants can only partially ac-

542 count for the delay and uncertainties associated with guessing.

General Formulation for the Models

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

545 density function:

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

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

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

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

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

550 able x, with a mean (μ) and standard deviation (σ). $F_X(b)$ is the normal cumulative den-

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

552 Throughout, capitalized variables denote normally distributed random variables. Addi-

553 tionally, lowercase variables such as x refer to the realization of the random variable X.

554 The lowercase notation simply indicates that the value is known and is not a random

555 variable.

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

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

558 random variable drawn from the stimulus's movement onset distribution (**Eq. 4**) and T

559   as the random variable drawn from the transition time distribution (**Eq. 5**).

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

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

560   Consider s and t as the realizations of random variables S and T for a single trial. On

561   any specific trial, a decision-maker will react if the stimulus movement onset is before the

562   transition time (i.e., $s < t$). Conversely, the decision-maker will guess at the transition

563   time if the stimulus has not moved by the transition time (i.e., $s > t$). Thus, the probability

564   that a participant will react or guess depends on the participants choice of a transition

565   time mean (τ). Specifically, the probability that the participant will react is the probability

566   that the random variable T is greater than S.

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

567   The probability that the participant will guess is the probability that the random vari-

568   able T is less than S.

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

569   As a result, a decision-maker only reacts to the portion of the stimulus's distribution

570   that is prior to their transition time. Thus, the participant reacts to a truncated distribution

571   of the stimulus movement onset. The truncated stimulus movement onset distribution

572   is generated from only taking the random variable S if it is less than the random variable

573   T. We can then define an indicator function ($\mathbb{1}_{s<t}$), which is equal to one if the realized

574   value s is less than t and zero otherwise:

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

575   The mean of the truncated stimulus movement onset distribution ($\mu_{S_{react}}$) can be cal-

576   culated by combining the indicator function and the method of moments. We start by

577   calculating the expected value of the random variable S, which is the integral from $-\infty$

578 to ∞ of the value s multiplied by the probability density function $f_S(s)$.

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

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

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

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

582 s depends on t, we calculate the mean of the truncated stimulus movement onset dis-

583 tribution by integrating over every possible combination of s and t. Inside the double

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

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

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

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

588 that S is less than T. The mean (first moment) of the truncated stimulus movement onset

589 distribution is

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

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

591 onset distribution, where variance is the second moment, by:

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

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

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

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

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

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

597 ulus movement onset mean ($\mu_{S_{react}}$) plus the participant mean response time (μ_{rt}). Like-

598 wise, the standard deviation of participant reaction movement onset ($\sigma_{mo_{react}}$, **Eq. 13**) is

599 the square root of the variance of the truncated stimulus movement onset distribution

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

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

601

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

602   Here, μ_{rt} represents the time to process the stimulus movement plus the neurome-

603 chanical delay (μ_{nmd}). For the No Switch Time Model, the participant mean guess move-

604 ment onset ($\mu_{mo_{guess}}$, **Eq. 14**) is the sum of the participant transition time τ and the mean

605 neuromechanical delay μ_{nmd}. The participant standard deviation guess movement onset

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

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

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

608

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

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

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

611 uncertainty,

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

612

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

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

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

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

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

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

618 knowledge for the Partial Switch Time Model.

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

620 and the guess target reach time mean ($\mu_{reach_{guess}}$) and standard deviation ($\sigma_{reach_{guess}}$) as

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

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

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

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

621 To obtain the probability of reaching the target given the participant has either re-

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

623 distribution of target reach times according to

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

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

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

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

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

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

627

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

628 We can now define the conditional probabilities for three outcome metrics: indeci-

629 sion, win, and incorrect. The conditional probability of an indecision given the participant

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

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

632 reach the target within the time constraint:

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

633

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

634 To define a win or incorrect trial, we need the conditional probability of selecting

635 the correct target given the participant has either reacted ($P(Correct|React)$) or guessed

636 ($P(Correct|Guess)$). The probability of selecting the correct target when the participant

637 reacts is 100% (**Eq. 28**). The probability of selecting the correct target when the partici-

638 pant guesses is 50% (**Eq. 29**).

639

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

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

640 The conditional probability the participant wins given they react ($P(Win|React)$) or

641 guess ($P(Win|Guess)$) is the probability that they reach the target within the time con-

642 straint, and they select the correct target:

643

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

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

644 The conditional probability the participant is incorrect given they react ($P(Incorrect|React)$)

645 or guess ($P(Incorrect|Guess)$) is the probability that they reach the target within the time

646 constraint and they select the wrong target:

647

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

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

648 Finally, we define the final probability of wins ($P(Win|\tau)$), indecisions ($P(Indecision|\tau)$),

649 and incorrects ($P(Incorrect|\tau)$), by considering their and their associated conditional

650 probabilities (**Eq. 26-33**) and the probability of reaching and guessing given a transition

651 time (τ), as

$$P(Win|\tau) = P(React|\tau) \cdot P(Win|React)$$

$$+ P(Guess|\tau) \cdot P(Win|Guess) \tag{34}$$

$$P(Indecision|\tau) = P(React|\tau) \cdot P(Indecision|React)$$

$$+ P(Guess|\tau) \cdot P(Indecision|Guess) \tag{35}$$

$$P(Incorrect|\tau) = P(React|\tau) \cdot P(Incorrect|React)$$

$$+ P(Guess|\tau) \cdot P(Incorrect|Guess). \tag{36}$$

652 *Decision Policy*

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

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

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

656
$$R_{win} = 1 \tag{37}$$

657
$$R_{indecision} = 0 \tag{38}$$

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

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

659 probability of that outcome, which is

$$\mathbb{E}[R|\tau] = P(Win|\tau) \cdot R_{Win}$$

$$+ P(Incorrect|\tau) \cdot R_{Incorrect}$$

$$+ P(Indecision|\tau) \cdot R_{Indecision}. \tag{40}$$

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

661 that maximizes expected reward:

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

662 **Model Parameter Estimation and Fitting Procedure**

663 As a reminder, we had three models: No Switch Time Model, Full Switch Time Model,

664 and Partial Switch Time Model. Each of these models had full knowledge of the reaction

665 time mean and standard deviation, neuromechanical delay mean and standard devia-

666 tion, movement time mean and standard deviation, and the stimulus movement onset

667 distribution. These parameter values were estimated from experimental data by boot-

668 strapping the meansfrom the response time experiment (μ_{rt}, σ_{rt}), timing experiment (σ_{τ}),

669 and **Experiment 1** (μ_{mt}, σ_{mt}). We describe the bootstrap procedure below. Neurome-

670 chanical delay (μ_{nmd}) and uncertainty (σ_{nmd}) were estimated from prior literature.[57,58,59]

671 　　We used both a warm-start initialization and bootstrap procedure (see below) to de-

672 termine the switch time mean (μ_{switch}) and uncertainty (σ_{switch}), as well as the decision

673 policy's knowledge of the switch time mean ($\hat{\mu}_{switch}$), switch time uncertainty ($\hat{\sigma}_{switch}$), and

674 timing uncertainty ($\hat{\sigma}_{\tau}$).

675 *Warm-Start Initialization*

676 The fitting procedure for the Full Switch Time Model and Partial Switch Time Model

677 began with a "warm-start" to find an initial set of μ_{switch}, σ_{switch}, $\hat{\mu}_{switch}$, $\hat{\sigma}_{switch}$, and $\hat{\sigma}_{\tau}$.[37,38]

678 Here the remaining parameters estimated from experimental data were set as the group

679 level means. We found the best-fit parameters that led to the lowest loss between model

680 outputs ($Model_{i,j}$) and group data means ($Data_{i,j}$) according to

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

681 where i corresponds to experimental condition and j corresponds to each dependent

682 measure (i.e., movement onset, standard deviation of participant movement onset, wins,

683 indecisions, and incorrects). The fitting procedure was repeated 1,000 times to avoid

684 local minimums. From these 1,000 optimizations, we used the set of parameters that

685 resulted in the lowest loss as the initial guess for our bootstrap procedure. Model fitting

686 was performed using the Powell algorithm in the Minimize function from the Scipy Python

687   library.

688   *Bootstrap Procedure*

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

690   times.[37,38,54,55] We used the mean of the bootstrapped participant data for each of the

691   parameter values that were estimated from data. For each bootstrap iteration, the op-

692   timization process selected the free parameters for the Full Switch Time Model (μ_{switch},

693   σ_{switch}) and Partial Switch Time Model (μ_{switch}, σ_{switch}, $\hat{\mu}_{switch}$, $\hat{\sigma}_\tau$, $\hat{\sigma}_\tau$) that minimized the

694   loss function (**Eq. 44**).

695   **Model Parameter Values**

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

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

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

699   and Full Switch Time Model were both optimal in the sense that they had perfect knowl-

700   edge of all parameters. That is, the value that determined model outputs was equal to

701   the value used by the decision policy. Parameter values for reaction time mean, reaction

702   time uncertainty, movement time mean, movement time uncertainty, and timing uncer-

703   tainty were all calculated from participant data on each bootstrap iteration: reaction time

704   mean (247.4 ms; [239.2, 256.35]), reaction time uncertainty (38.5 ms; [35.7, 41.4]), move-

705   ment time mean (171.7 ms; [157.6, 197.2]), movement time uncertainty (25.4 ms; [22.2,

706   28.7]), and timing uncertainty (77.8 ms; [69.4, 86.6]). The No Switch Time Model had no

707   parameters to fit, and the decision policy had full knowledge of all of these parameters.

708   The Full Switch Time Model fit the switch time mean and switch time uncertainty and

709   the decision policy had full knowledge of all parameters. The bootstrapped mean of the

710   switch time delay parameter was 0.95 ms with a 95% confidence interval of [0.21, 2.20].

711   The bootstrapped mean of the switch time uncertainty parameter was 103.20 ms with a

712   95% confidence interval of [97.77, 115.31].

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

time uncertainty. Critically, this model did not have full knowledge of these parameters, so the value that the decision policy used to select the optimal time was fit separately from the value that was used to determine the model outputs. Note that the timing un-certainty value used for model outputs is from experimental data, but this model allowed the knowledge of the timing uncertainty to be a fit parameter. The values that were used for model outputs were: timing uncertainty (77.83 ms; [69.4, 86.8]), switch time mean (21.10 ms; [1.46, 63.71]), switch time uncertainty (134.73 ms; [111.22, 155.06]. The val-ues that were used by the decision policy were: timing uncertainty (1.65 ms; [0.08, 4.63]), switch time mean (9.0 ms; [0.00, 16.65]), switch time uncertainty (40.4 ms; [34.54, 48.02]). Critically, the fitting procedure for the Partial Switch Time Model selected the decision policy's values for the switch time mean, switch time uncertainty, and timing certainty to be less than the values that impact the model outputs, indicating that humans have imperfect knowledge of these parameters.

Supplementary C: Model Results

727
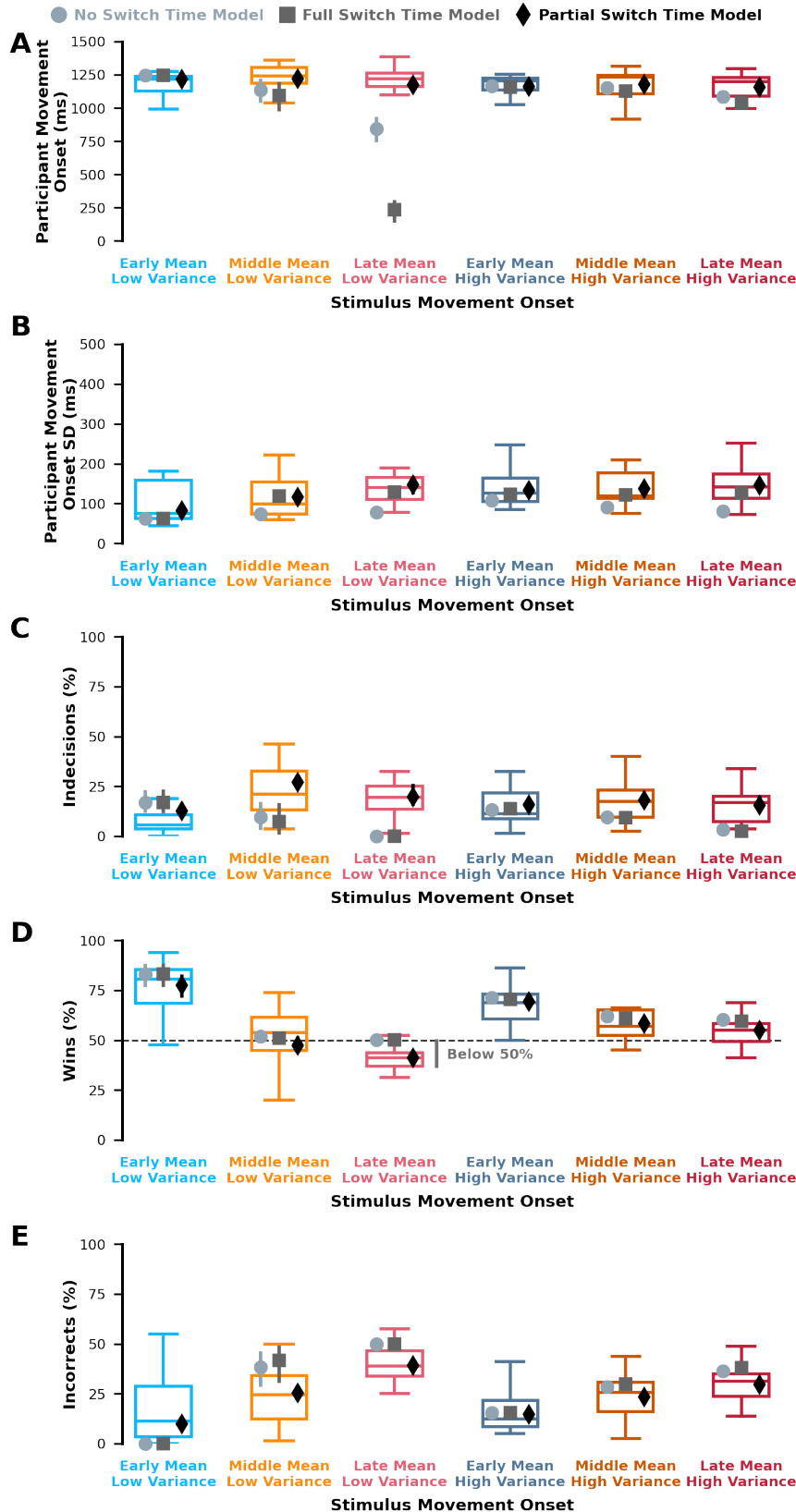
**Supplementary Figure 3: Model Outputs**. Here we show model fits for the No Switch Time Model (light gray circles), Full Switch Time Model (dark gray squares), and the Partial Switch Time Model (black diamonds) for **A)** participant movement onset time, **B)** participant movement onset time standard 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.
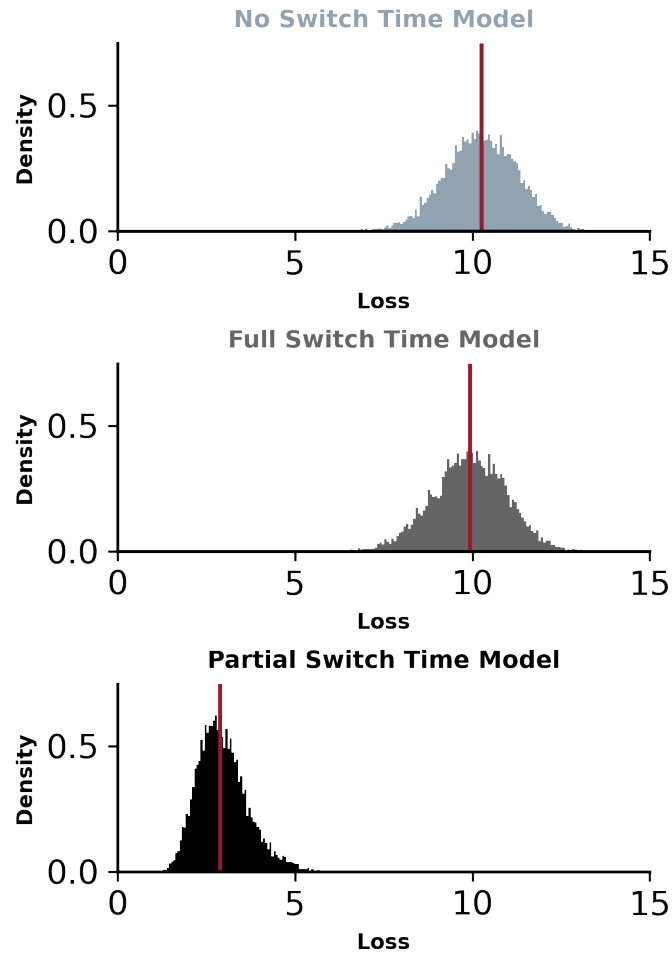
Supplementary Figure 4: Model Losses. Here we show histograms of each of our model's bootstrapped losses. Loss was calculated as the normalized mean absolute error between the model prediction and experimental data for each of the following metrics: movement onset, movement onset standard deviation, 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 D: Response Time Task

For the response time task (**Supplementary Figure 5**), 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
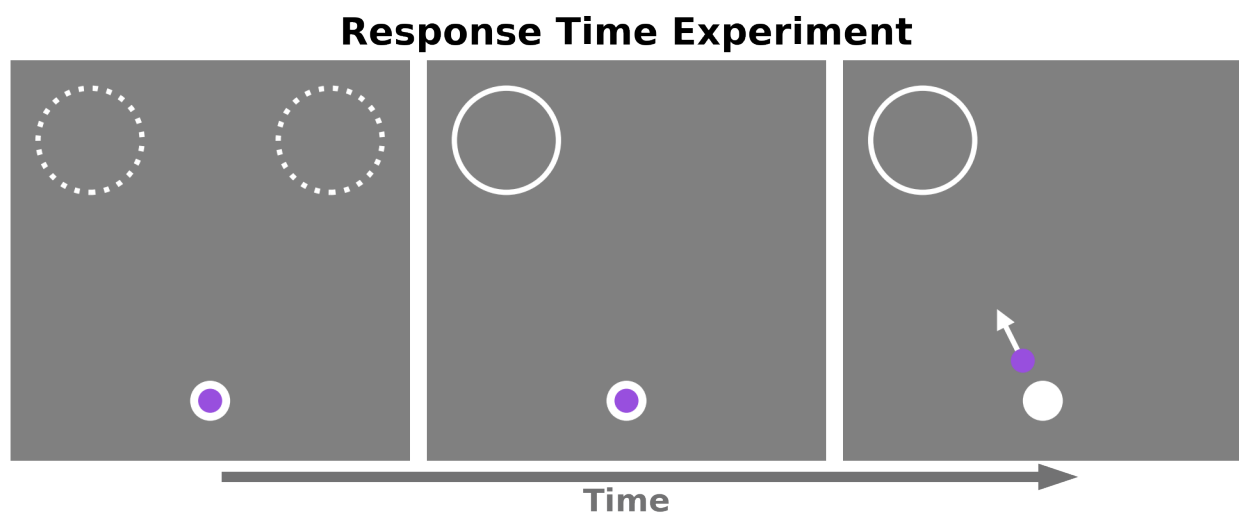
Time

Supplementary Figure 5: 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 E: 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

Time
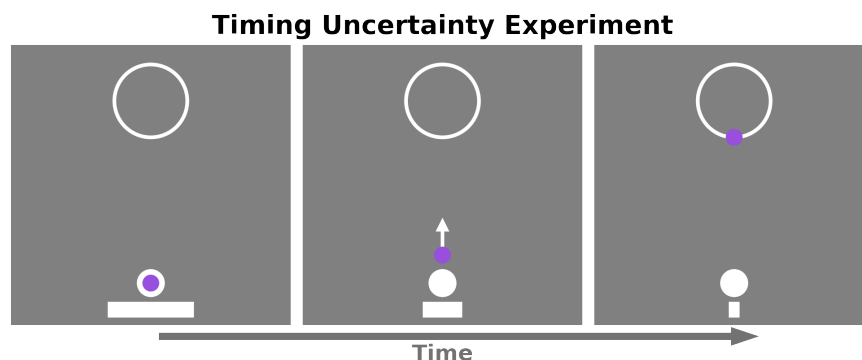
Supplementary Figure 6: Timing Uncertainty Experiment. One of two potential targets (dashed white rings; not visible to participants) would appear on the screen. Once a target appeared (solid white ring), participants were instructed to rapidly move their cursor to hit the displayed target. We used the mean and standard deviation of response times as model parameters in the optimal transition models.

756 Supplementary F: Guess Decisions
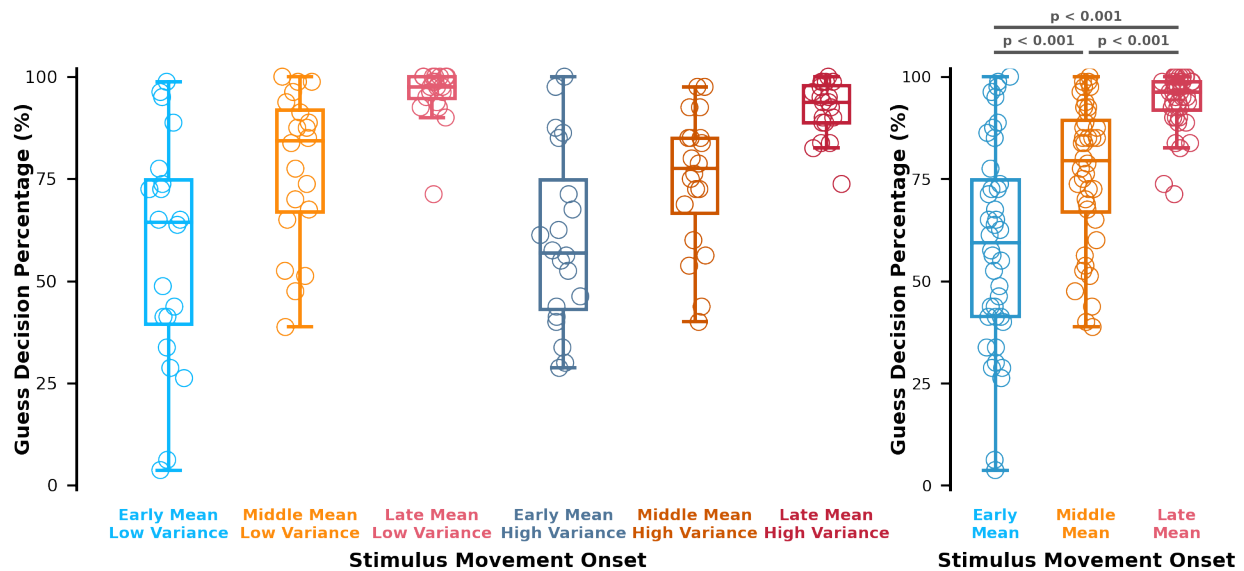
Supplementary Figure 7: Guess Decision Percentages for Experiment 1. Estimated percentage of guess decision percentages (y-axis) for each experimental condition (x-axis). During **Experiment 1** participants were rewarded for successful trials and experienced a time constraint. Thus, we would expect participants to have faster response times in **Experiment 1** than in the Response Time task.[60,61] 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.