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1 **Rodents monitor their error in self-generated duration on a single trial basis**

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22 contributed to the interpretation of the results. TWK prepared the first version of the
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24 and manuscript.

25
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30
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32 Main Text

33 Figures 1 to 4

1 **Abstract**

2

3 A fundamental question in neuroscience is what type of internal representation leads to
4 complex adaptive behavior. When faced with a deadline, individuals' behavior suggests that
5 they represent the mean and the uncertainty of an internal timer to make near optimal time-
6 dependent decisions. Whether this ability relies on simple trial-and-error adjustments, or
7 whether it involves richer representations, is unknown. Richer representations suggest a
8 possibility of error monitoring, that is, the ability for an individual to assess its internal
9 representation of the world and estimate discrepancy in the absence of external feedback.
10 While rodents show timing behavior, whether they can represent and report temporal errors
11 in their own produced duration on a single trial basis is unknown. We designed a novel
12 paradigm requiring rats to produce a target time interval and subsequently evaluate its error.
13 Rats received a reward in a given location depending on the magnitude of their timing errors.
14 During the test-trials, rats had to choose a port corresponding to the error magnitude of their
15 just-produced duration to receive a reward. High choice accuracy demonstrates that rats kept
16 track of the values of the timing variables on which they based their decision. Additionally, the
17 rats kept a representation of the mapping between those timing values and the target value,
18 as well as the history of the reinforcements. These findings demonstrate for the first time error
19 monitoring abilities in evaluating self-generated timing in rodents. Together these findings
20 suggest an explicit representation of produced duration and the possibility to evaluate its
21 relation to the desired target duration.

22

23 **Significance**

24

25 Evaluating the richness of representations mapping animal's experience of time and space is a
26 profound problem in neuroscience. Animals could base their behavior only on the recent
27 rewards, but they also could rely on more complex representations of their own behavior.
28 When faced with a deadline, individuals seem to adjust their decision based on the overall
29 knowledge of their performance. We evaluated whether rats monitor timing of their own
30 actions or adapt only based on recent rewards. Rats accurately reported the magnitude of their
31 timing error in self-generated time intervals. The results for the first time show that rats track
32 their own timing errors, deepening our understanding of error monitoring abilities in rodents
33 and richness of their representation of elapsed time.

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1 Introduction

2
3 In neuroscience, a fundamental question is how rich the internal representation of an
4 individual's experience must be to yield adaptive behavior. Let us consider a hungry individual
5 in need of finding food fast: the individual may adopt a trial-and-error foraging strategy to
6 maximize reward, but may also, to maximize its efficiency, represent rich experiential variables,
7 such as how much time it takes to reach a source of food. Both, representing elapsed time and
8 monitoring its inherent uncertainty plays an important role in adaptive behavior, learning, and
9 decision making (Balci et al., 2009). When representing these variables, the sources of
10 uncertainty are both exogenous (stimuli-driven) and endogenous (neural implementation). The
11 mapping of exogenous sources of temporal uncertainty has been well described in timing
12 behavior: for instance, mice can adjust their behaviors to the width of the distribution of
13 temporal intervals provided through external stimuli (Li & Dudman, 2013). On the other hand,
14 the endogenous sources of uncertainty for time perception are less understood and more
15 difficult to address.

16
17 Evidence that animals are sensitive and have access to the internal uncertainty of elapsed time
18 comes from a task in which the individual must produce a required target duration using a
19 lever-press or a key-press (Balci et al., 2009; Kheifets et al., 2017; Kheifets & Gallistel, 2012). In
20 a task where individuals must produce an interval of fixed duration to obtain a reward (Figure
21 1A), a plausible strategy to maximize reward would be to set the produced duration to be
22 longer than the required target duration so as to allow a margin of error (internal target
23 duration, Balci et al., 2009). This is because the larger an individual's representational
24 uncertainty, the larger the margin of error to maximize the reward. Consistent with this, studies
25 have shown that the magnitude of error in produced intervals varies with the magnitude of
26 temporal uncertainties (Çavdaroğlu, Zeki, Balci, 2014; Freestone et al., 2015), and participants
27 with larger temporal uncertainty set larger margins of errors (Fig. 1B; Supp. Fig. 2; Balci et al.,
28 2009; Freestone et al., 2015). The observed optimization of timing behavior begs the question
29 of how rich the representation of elapsed time must be.

30
31 A trial-and-error strategy would predict that near optimal behavior can be parsimoniously
32 explained by adaptation, so that timing behavior would fluctuate around the required duration.
33 The representational view would predict that uncertainty and trial-to-trial errors are
34 experiential variables used by the animals to monitor their timing behavior.

35
36 To settle the question of whether rodents can monitor their timing errors relative to their target
37 on a trial-by-trial basis, we developed a novel task inspired by human work. Humans required
38 to generate a time interval can also reliably report the magnitude of their errors and their sign
39 (Kononowicz et al., 2019), i.e., they can evaluate by how much (magnitude) their generated
40 duration was too short, or too long (sign), with respect to the target duration. Humans can also
41 report how confident they are in their timing behavior (Akdoğan & Balci 2017). We tested here
42 these temporal cognitive abilities in rats, which were required to produce a time interval and
43 correctly report, in order to obtain a reward, the magnitude of their timing errors on some test-
44 trials. We show that rats correctly reported the magnitude of their timing error, suggesting that
45 their timing behavior uses explicit representations of time intervals together with their
46 uncertainty around the internal target duration.

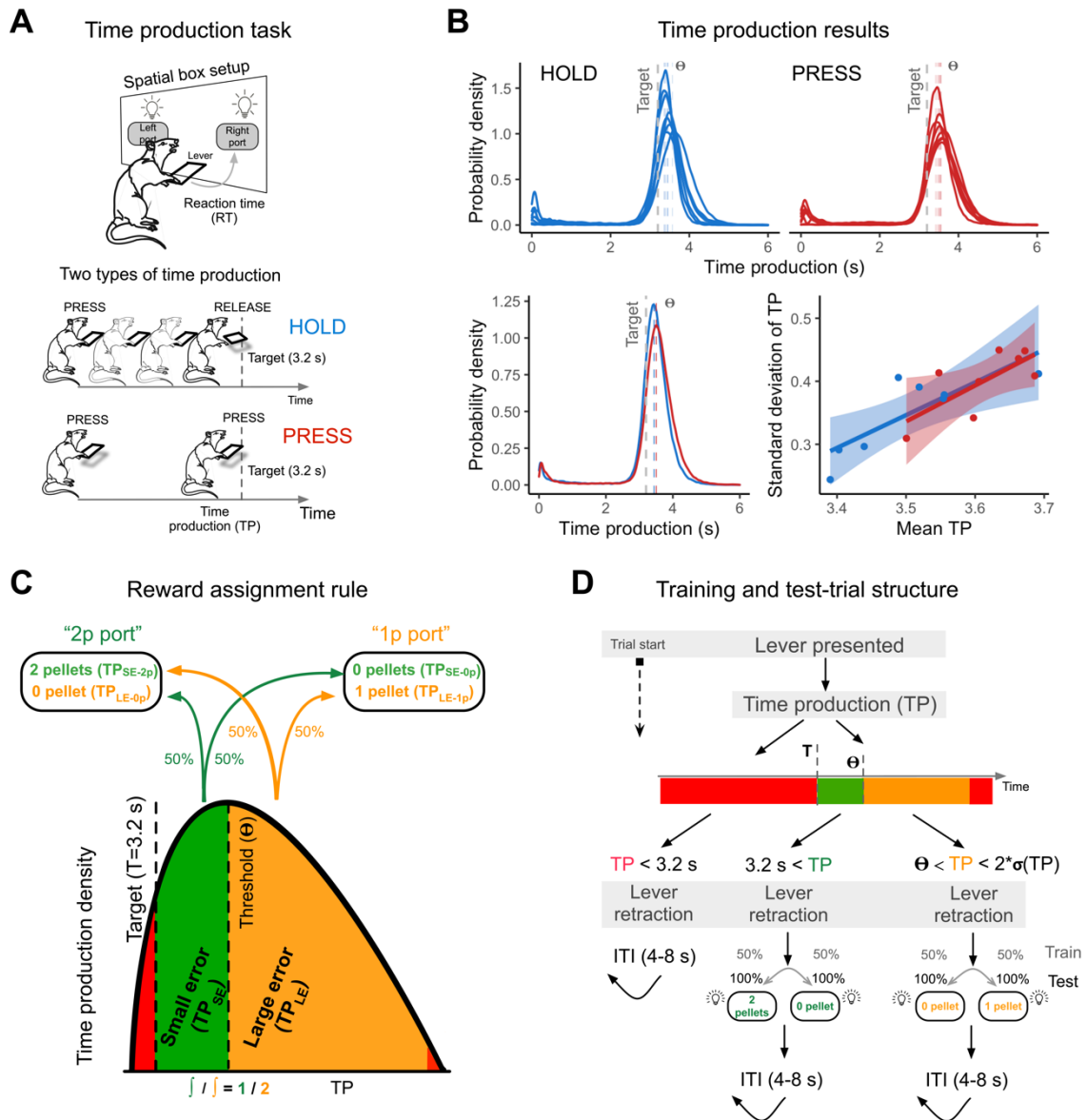


Figure 1. The time production task and error monitoring protocol.

(A) Schematic of a box arrangement with a lever available in the middle of the panel and reward ports on the left and right side of the lever. Reward availability was signaled by the port lit, depicted by the lightbulbs. Reward delivery was triggered by rats' nose poke in the reward port. Depending on the group assignment, rats had to either hold the lever pressed for a minimum of 3.2s (HOLD group), or press the lever twice with a minimal delay (3.2 s) between two presses (PRESS group).

(B) Time production (TP) performance, in error monitoring test sessions, follows Weber's law for both groups, with signatures of optimality. Upper panel depicts probability density functions over TPs for each individual rat in HOLD (blue) and PRESS (red) groups. Thresholds Θ (blue and red dashed lines HOLD and PRESS group, respectively) are plotted for each individual. Bottom left panel depicts average probability density functions over TPs for HOLD and PRESS groups superimposed. Note the distribution shift and width shrinkage for HOLD group. Bottom right panel: for each rat, $\mu(\text{TP})$ is plotted against $\sigma(\text{TP})$. Both at the individual and at the group level the PRESS rats showed larger $\mu(\text{TP})$ and $\sigma(\text{TP})$, visible as an upward right shift of the red curve. This pattern indicates that rats make their choices optimally, taking into account their level of TP variability. The results hold within each rat and across sessions (Supp. Mat. S3).

1 (C) Schematic depiction of how rewards were assigned to specific parts of TP distribution. Green color is used for
2 'small error' (SE) trials and orange color for 'large error' trials. Red color indicates TPs that were out of reward
3 range. The arrows indicate probabilistic assignment of TP type (SE or LE) to left and right ports, on training trials.
4 On test trials, the food-port assignments remained, but both ports were available and, thus, the amount of reward
5 was driven by rat's choice.

6
7 (D) Schematic of a trial structure. From the top to bottom, the succession of task events is depicted. They alternate
8 along TP-axis (color bar with red, green, and orange) and show different scenarios that are determined by rats'
9 performance on TP in single trials. Inter-trial-interval (ITI) is the last event in a single trial sequence.

1 Results

2

3 *Rats produce time intervals optimally*

4

5 Two groups of rats were trained to produce a minimum Target duration ($T = 3.2s$) by pressing
6 a lever twice to demarcate T (PRESS group), or by pressing a lever for T amount of time (HOLD
7 group). Producing at least T provided access to a reward (Fig. 1A). All rats produced the required
8 time interval T as all distributions of duration time productions (TP) peaked after T (Fig. 1B).
9 Higher rewards were assigned to more accurate TPs to maximally exploit animal's temporal
10 precision and use this temporal precision efficiently in a reward assignment rule (Fig. 1C).
11 Consistent with Weber's law in duration reproduction (Gallistel & Gibbon, 2000; Gibbon, 1992;
12 Buhusi & Meck, 2005), the standard deviation of TPs ($\sigma(TP)$) increased with the mean TP ($\mu(TP)$;
13 Fig. 1B bottom panel, Supp. Mat. S3; Supp. Fig. 3; $t(586) = 15.4$, $p < 10^{-10}$). Comparable slopes
14 in PRESS and HOLD groups were found (Fig. 1B, $\Delta AIC = 0.3$, $p = 0.155$). As $\sigma(TP)$ shrank over
15 sessions (Supp. Fig. 3) and across individuals (Fig. 1B), the distance between T and $\mu(TP)$ shrank
16 as well. This covariation strongly suggests a near optimal exploitation of timing uncertainty by
17 the animals. Indeed, the animals displayed behavioral patterns suggesting that they adapt their
18 mean responding on the basis of their timing uncertainty (Balci et al., 2009; Kheifets et al.,
19 2017; Kheifets & Gallistel, 2012). This phenomenon has two plausible explanations: (1) the
20 animals could adapt their TPs by trial-and-error (Simen & Balci, 2011; Luzzardo et al., 2013),
21 based exclusively on the memorized association of different rewards with different TP lengths
22 (Jozefowicz et al., 2009); (2) alternatively, their behavior could be driven by model-based,
23 explicit representations of TP and their relation to internal target duration (Tosun et al., 2016),
24 which implies a tracking of their temporal error on a single trial basis. Hence, we explore the
25 two possibilities below.

26

27 *Rats choose accurately on test-trials, expressing error monitoring*

28

29 To assess temporal error monitoring, we developed a novel behavioral paradigm in which, on
30 each trial, rats first produced a duration (TP) and subsequently reported its accuracy (i.e., how
31 far the TP is from T). Rats were trained with the reward assignment rule (Fig. 1C) which
32 associated TP error (small error: TP_{SE} trials vs. large error: TP_{LE} trials) with reward delivery of
33 different sizes (TP_{SE-2p} and TP_{LE-1p} trials), or reward absence (TP_{SE-0p} and TP_{LE-0p} trials) in one of
34 two ports. A given port delivered 1p after a large error (TP_{LE-1p}) but 0p after a small error (TP_{SE-0p} ,
35 Fig. 1C, '1p port'), whereas the other port delivered 2p after a small error (TP_{SE-2p}) but 0p
36 after a large error (TP_{LE-0p} , Fig. 1C, '2p port'). Before introducing test-trials, the pattern of
37 reaction times (RT) in the control training trials in which only one port was lit showed that rats
38 reached the port faster when expecting a reward delivery based on their TP error (Supp. Mat.
39 S4, Supp. Fig. 4A). Furthermore, when probed on test trials with both reward ports lit up, the
40 rats were rewarded if they chose according to the rule (Fig. 1C), thus maximizing reward rate.
41 Rats increased their choice reaction times on test-trials compared to training-trials, indicating
42 typical choice behavior (Supp Fig. 4B). Test-trial accuracy (proportion of correct choices) is a
43 direct measure of temporal error monitoring, as the reward rule was conditional on the
44 magnitude of the TP error. Note that the reward assignment rule and threshold adjustment
45 were constructed such that overall reward was similar in both ports. Furthermore, if rats
46 exhibited a bias to choose 2p port on all test trials, the accuracy would result in the chance level
47 accuracy scores (0.5). Indeed, we did not observe strong association between accuracy and

1 pellet ratio on per rat, per session basis ($\beta = -1.32$, $SE = 2.06$, $t(1781) = -0.64$, $p = 0.53$). From
2 Fig. 2A it is evident that accuracy on test trials (collapsed over 1p and 2p ports) was above
3 chance level for all rats (each animal above 50% chance level, $p < 0.05$, two-sided Wilcoxon test,
4 see Supp. Table 1). Additionally, the PRESS group exhibited higher test-trial accuracy (Fig. 2B; β
5 = 0.04, $SE = 0.007$, $z(5967) = 5.46$, $p < 10^{-7}$). As the PRESS group was also the one in which
6 animals showed poorer TP performance, it suggests better choice performance in animals with
7 larger variability. To test this hypothesis we assessed the relationship between choice
8 performance and standard deviation across sessions by fitting a model where choice accuracy
9 was predicted by standard deviation with inclusion of group factor. The effect of standard
10 deviation ($\beta = 0.018$, $SE = 0.022$, $t(567) = 0.81$, $p = 0.417$) and interaction between std and
11 group ($\beta = -0.003$, $SE = 0.029$, $t(600) = -0.122$, $p = 0.902$) were not significant. That suggested
12 that the difference in choice accuracy between groups was not driven by differences in
13 variability but was related to the different motor sequences required to produce duration. As
14 rodents may use motor routines to support temporal judgments (Gouvêa et al., 2014; Killeen
15 & Fetterman, 1988; Machado, 1997; Safaie et al., 2020), it raises the question to what extent
16 motor routines could contribute to interval timing and error monitoring.

17
18 As the test-trial accuracy neglects a continuous link between choice and TP error, we verified
19 that the rats showed an increased probability of 1p choice as a function of TP error (Fig. 2CD),
20 with GLMM predicting the probability of choosing 1p port vs. 2p port given the TP error (Fig.
21 2E; $\beta = 3.29$, $SE = 0.30$, $z(19512) = 11.01$, $p < 10^{-15}$). Rats exhibited choice uncertainty for TPs
22 close to their internal threshold (Fig. 2CDE). Of course, the better the internal threshold aligns
23 with Θ threshold, the higher the chances for higher choice accuracy.

24
25 Overall, both analyses showed that rats chose between 1p and 2p options with relatively high
26 accuracy, suggesting that subjects have a representation of the relation between the duration
27 of the just-produced interval and the interval, longer than required interval, chosen based on
28 the level of temporal uncertainty. However, the representation of the required interval, the
29 margin of error, and the representation of the time elapsed during an attempt to produce the
30 required interval, all have limited precision. The uncertainty in the port choice must reflect the
31 uncertainties in the first order variables, as listed, on which it depends. Therefore, near perfect
32 accuracy is not to be expected.

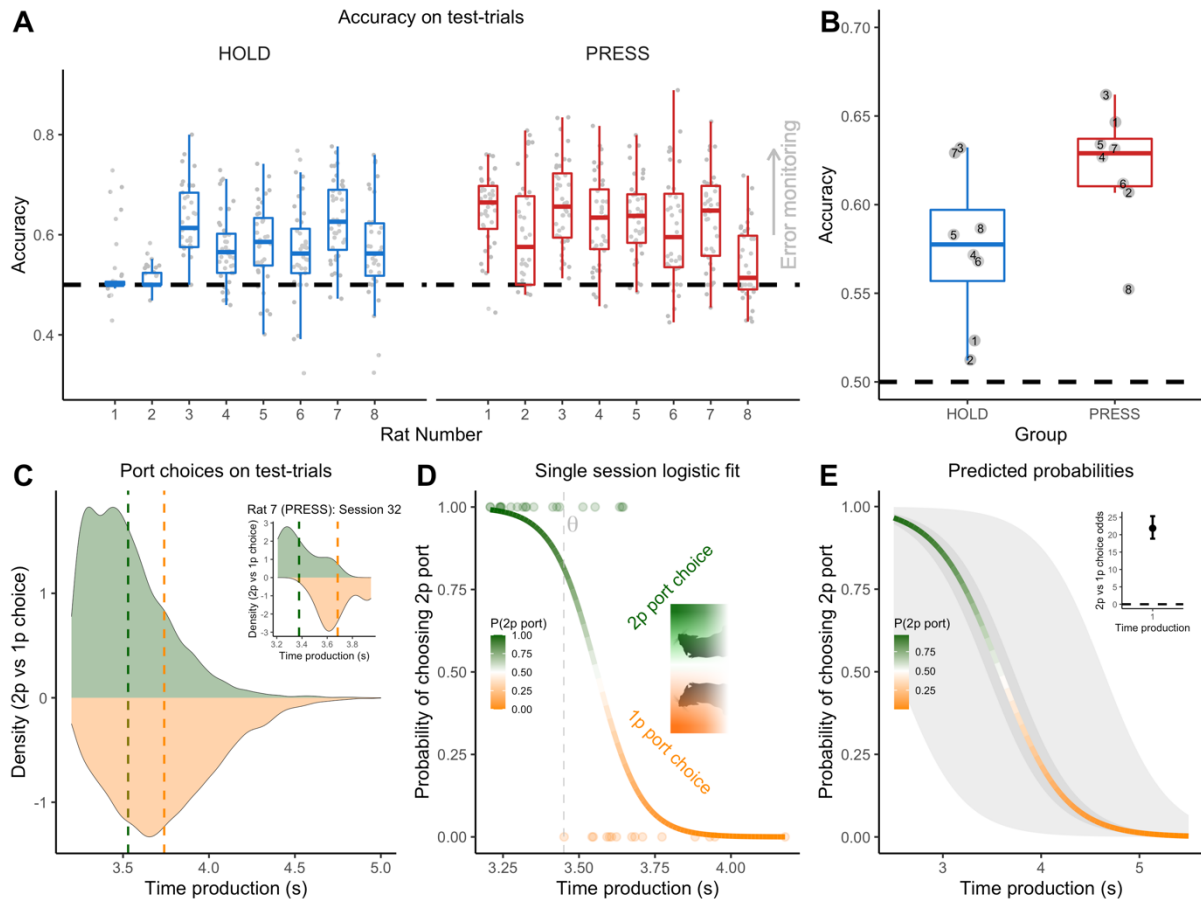


Figure 2. Rats report temporal errors by choosing accurately on test-trials.

(A) Grey data points show session-by-session accuracy on test trials for individual rats, that is, the proportion of test trials in which a rat chose a port at which a reward will effectively be delivered. The 1 pellet and 2 pellets reward trials were averaged together. A strategy in which only one port would be chosen would result in chance level (0.5) accuracy. Each column shows the results for one rat across all experimental sessions for the two groups of rats. All rats chose significantly above the chance level indicating the ability to monitor temporal errors.

(B) Accuracy on test-trials plotted separately for HOLD and PRESS group. Notably PRESS group achieved higher level of accuracy.

(C) Probability density distribution over TPs on test-trials plotted as a function of rats' choices. Time productions reported by rats as 2p trials are plotted in green and trials classified by rats as 1p trials are plotted in orange. The mean of each distribution is indicated by a dashed vertical line of corresponding color. The 1p distribution (orange) is shifted with respect to the 2p distribution (green), clearly indicating that rats' reports are a function of TPs. The main plot shows density across all rats and sessions. The inset plot shows one sample session of one rat.

(D) Logistic function fitted to a sample session of one rat from panel C (inset). As the curve descends, TP duration increases together with the probability of choosing 1p port on test trials and the probability of choosing 2p port decreases. The descent of the logistic function signifies that as TP duration increases the probability of choosing 2p on test trials decreases. The scale ranges from green to orange, corresponding to reward assignment (Fig. 1C). Data points at the top (orange, 1p choice) and at the bottom (green, 2p choice) of the plot show individual TPs, whereas the color code signifies 1p and 2p choices of rat '7' in session 32.

(E) Generalized linear mixed effect model fit including TP as predictor. Data from 14 rats were used to fit the model. Two types of shaded areas display confidence intervals at a population level. The narrow shading displays population level confidence intervals. The wider shading displays population-level predictions with consideration of uncertainty in the variance parameters (Johnson & O'Hara, 2014). Thus, the wider shading can be considered as prediction intervals (Francq et al., 2019). Similarly, as in panel D, color progression from green to orange depicts

increasing probability of 1p port choice as a function of TP. The inset model displays obtained choice odds of TP predictor.

1 Rats keep track of temporal errors and reward history

2

3 We next investigated whether the rats used sources of information other than TP errors to
4 choose accurately on test trials. Recent work showed that local mean or variance of TP is not
5 stable over time in monkeys (Wang & Jazayeri, 2020) or in humans (Kononowicz et al., 2018).
6 This non-stationarity of time production was also observed here, as illustrated in a sample plot
7 (Fig. 3A, Supp. Mat. S7) depicting changes in local mean of TP (we refer to the moving mean of
8 the last n trials as $\mu(TP_n)$ over the course of one sample session). We hypothesized that rats
9 could use fluctuating $\mu(TP)$, when faced with test-trials, by keeping track of previous trials.
10 Indeed, rats track reward history of previous trials (Gallistel et al., 2001), also in a situation in
11 which rewards were delivered on the left or on the right side of a main port (Constantinople et
12 al., 2019; Hermoso-Mendizabal et al., 2020). In the current paradigm, the location of the
13 reward delivery port depended on the TP error. Thus, as TPs were non-stationary, rats could
14 have collected more rewards in just one port, in turn contributing to their choices. Indeed,
15 reward on previous trials contributed to test-trial choices (Supp. Mat. S5, Supp. Fig. 5A). We
16 tested the hypothesis that rats based their choices on the *reward history* (RH). For example, if
17 most of the recent trials were TP_{LE} , the rat has been rewarded in the 1p port, therefore
18 increasing a chance to choose that port. To quantify the reward history (RH) we calculated
19 relative amount of reward received in 1p and 2p ports. To test whether rats relied on *reward*
20 *history*, we used a logistic regression extending the basic model by adding the moving average
21 of n previous trials (μRH_n) to the model, as an expression of reward history. Keeping current TP
22 and adding reward history over a different number of preceding trials (μRH_{10} , μRH_{20} , μRH_{30} for
23 window sizes of 10, 20 or 30 trials) in the same model allowed assessing their relative
24 contributions to choice behavior. Independently of the number of trials considered – namely,
25 independently of the history window size - both current TP and μRH_n contributed to choice
26 behavior, as evidenced by large values of estimated choice odds (Fig. 3B; RH_n : $\beta = 0.60$, $SE =$
27 0.094 , $z(16423) = 6.37$, $p < 10^{-9}$; μRH_{10} : $\beta = 0.47$, $SE = 0.041$, $z(16423) = 11.34$, $p < 10^{-14}$; μRH_{20} :
28 $\beta = 0.35$, $SE = 0.064$, $z(16423) = 0.64$, $p = 10^{-7}$; μRH_{30} : $\beta = 2.35$, $z(16962) = 4.54$, $p < 10^{-5}$).

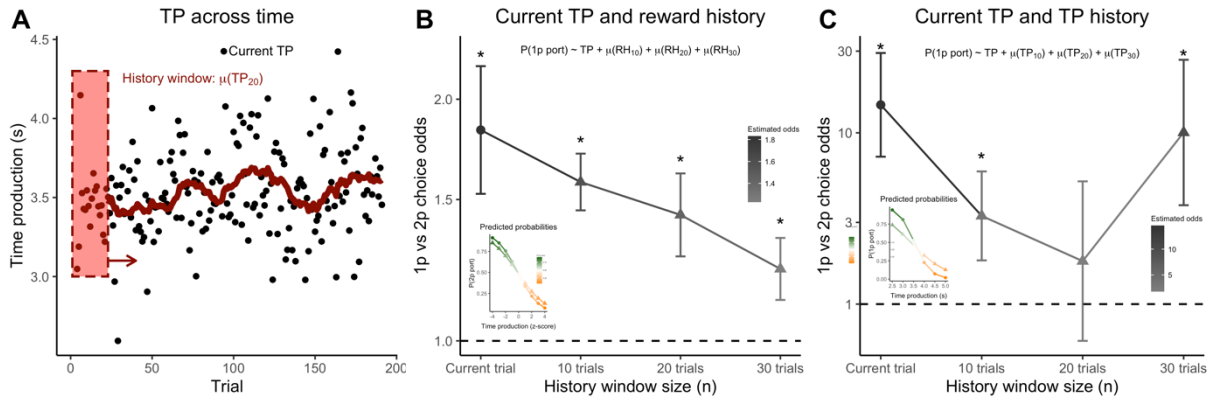
29

30 As the previous TPs can influence current TP (Wiener et al., 2015; Jazayeri & Shadlen, 2010;
31 Roach et al., 2017), we also considered the possibility that reward history due to previous time
32 productions (μTP_n) could influence choices on test-trials (Supp. Mat. S5, Supp. Fig. 5B). As the
33 amount of reward was conditional on TP, mean TP in n previous trials (μTP_n) is a proxy of reward
34 history, incorporating TP history. Indeed, both current TP and μTP_n contributed to choice
35 behavior, as evident in the large values of estimated choice odds (Fig. 3C; TP_n : $\beta = 2.66$, $z(16962)$
36 $= 7.45$, $p < 10^{-13}$; μTP_{10} : $\beta = 1.24$, $z(16962) = 3.86$, $p < 10^{-3}$; μTP_{20} : $\beta = 0.50$, $z(16962) = 0.91$, $p =$
37 0.36 ; μTP_{30} : $\beta = 2.35$, $z(16962) = 4.54$, $p < 10^{-5}$). Similar results were obtained for rewarded and
38 unrewarded trials (Supp. Fig. 6). Remarkably, both factors, TP and reward history, remained
39 significant, indicating that rats rely on both sources of information while choosing on test-trials.

40

41 Together, these results show that during choice behavior, rats take into account both factors:
42 their temporal error on the current trial (TP_n) and the reward history (μRH_n). Contribution of
43 both factors demonstrates the richness of representation of elapsed time, including error
44 monitoring abilities together with tracking previous behavioral outcomes.

1



2

3

4 **Figure 3. Rats keep track of temporal errors and reward history.**

5 (A) TPs (black) plotted across an experimental session (example). Shaded red square depicts a moving average
 6 window. The red trace marks the moving average of 20 TPs. That is, one data point of moving average is a result
 7 of averaging the preceding 20 trials. Fluctuation of moving average illustrates non-stationarity of TP.

8

9 (B) Results of GLMM fit including current TP and running average of last 10, 20, 30 rewards (Reward History). Data
 10 from 14 rats were used to fit the model. The formula in the plot shows specification of fixed terms in the GLMM.
 11 Asterisks indicate significant terms. Error bars display confidence intervals of estimated effects. Similar to Fig. 2E,
 12 the inset plot depicts logistic fit for Current trial (circle) and reward history (μRW_{10} , triangle).

13

14 (C) Results of GLMM fit including current TP and running average of last 10, 20, 30 TPs, as a proxy for reward
 15 history. Data from 14 rats were used to fit the model. Significant model terms indicate that rats keep track of
 16 temporal errors on current TP as well as TP history. Similar to Fig. 2E, the inset plot depicts logistic fit for Current
 17 trial (circle) and TP history (μTP_{30} , triangle).

1 *Inferred timing errors can guide future behavior.*

2
3 As rats reported their errors, we asked whether they used this ability to guide future behavior.
4 The first possibility is that temporal errors are only used in the experimental context to obtain
5 rewards. The second possibility is that temporal errors can also be utilized for error adjustment
6 on adjacent trials. Meck (1984) showed that when rats estimated 10 or 20 seconds time
7 intervals, the probability of trial-to-trial alternation between durations shorter, or longer, than
8 the median was above chance level. Alternation of shorter and longer trials in an ordered
9 sequence was a signature of ‘threshold hunting’, which we investigated in this dataset by
10 analyzing errors on consecutive trials, referred as relative errors (re , Fig. 4A). Focusing on
11 relative errors instead of raw TPs allows highlighting local adjustments of TP, which would
12 otherwise be confounded with other phenomena involving slow TP changes across multiple
13 trials. If there is no representation of relative error, there is no possible adjustment on the next
14 TP. Therefore, no relation between error on n -th TP (re_n) and error on n -th + 1 TP (re_{n+1}) would
15 be expected. In contrast, if temporal errors are utilized, small re_n will be followed by large re_{n+1} ,
16 and vice versa, resulting from adjustment of consecutive relative errors. We refer to this
17 behavior as ‘threshold hunting’ (Meck, 1988; Meck et al., 1984).

18
19 We controlled for the effects of reward magnitude on TP (Supp. Mat. 9) by focusing on triplets
20 of trials where the first two trials were accurate trials rewarded with 2 pellets (TP_{SE-2p}). As
21 reward magnitude calibrates performance variability on the next trial (Wang et al., 2019;
22 Dhawale et al., 2019), we verified that the TP variability on the 2 pellets trials was unaffected by
23 reward magnitude (Supp. Mat. 9, Supp. Fig. 9). re_n was calculated as the signed difference of
24 temporal error between the second and the first trial in each triplet (2nd TP_{SE-2p} - 1st TP_{SE-2p} ,
25 Fig. 4A). Likewise, re_{n+1} was calculated as the difference between the third and the second trial
26 in each triplet (3rd TP - 2nd TP_{SE-2p} , Fig. 4A). Each triplet resulted in one pair of re_n and re_{n+1} . We
27 split the re_n trials into short and long bins of the same count. Based on short and long re_n bins,
28 we then evaluated re_{n+1} (Fig. 4A). In line with the error monitoring hypothesis, we found that
29 re_{n+1} in long re_n bin were shorter than re_{n+1} in short re_n bin (Fig. 4B, $\beta = -0.096$, $t(2441) = -7.34$,
30 $p < 10^{-12}$). Thus, after being rewarded on the n -th trial with 2 pellets, rats adjusted their relative
31 error on the next trial, suggesting the ‘threshold hunting’ behavior.

32
33 If the ‘threshold hunting’ behavior is a behavioral proxy for error monitoring, the degree to
34 which individual rats exhibited hunting should be associated with error monitoring metrics:
35 test-trial accuracy and estimated choice odds given current TP and TP history. A hunting index
36 was calculated by subtraction of long bin re_{n+1} from short bin re_{n+1} . It is evident from the left
37 panel of Fig 4C that, the larger the hunting index, the larger the average accuracy (Fig. 4C; $t(12)$
38 $= 3.25$, $p = 0.007$; robust regression). As revealed by previous analyses, the overall test-trial
39 accuracy was influenced by two factors: current TP and TP history. To assess whether they
40 relate differently to the hunting index, we retrieved the estimated parameters of the GLMM
41 for TP and μTP_{30} for each rat. We chose μTP_{30} because this factor showed the highest estimates
42 among TP history factors in the previous analyses. If the degree of hunting is a proxy for error
43 monitoring, the larger the hunting index, the larger the current TP estimates should be; and
44 the opposite prediction holds for TP history (TP_{30}). As suggested by Fig. 4C (right panel), the
45 rats that relied more on the current TP also exhibited the largest hunting index ($t(11) = 7.44$, p
46 $< 10^{-4}$), whereas those who relied more on the TP history exhibited the smallest hunting index
47 ($t(11) = -4.19$, $p = 0.002$; Fig. 4C, right panel inset). The addition of TP_{30} to the model including

1 TP was statistically justified (Wald test: $W(1) = 17.58, p < 10^{-4}$). Together, while controlling for
2 the plausible effects of variance (Supp. Mat. 9), we demonstrated hunting behavior in rats. The
3 association of hunting behavior with indices of choice accuracy suggests that rats can use
4 estimated errors to guide future behavior, supporting a functional role of error monitoring in
5 guiding adaptive behavior.

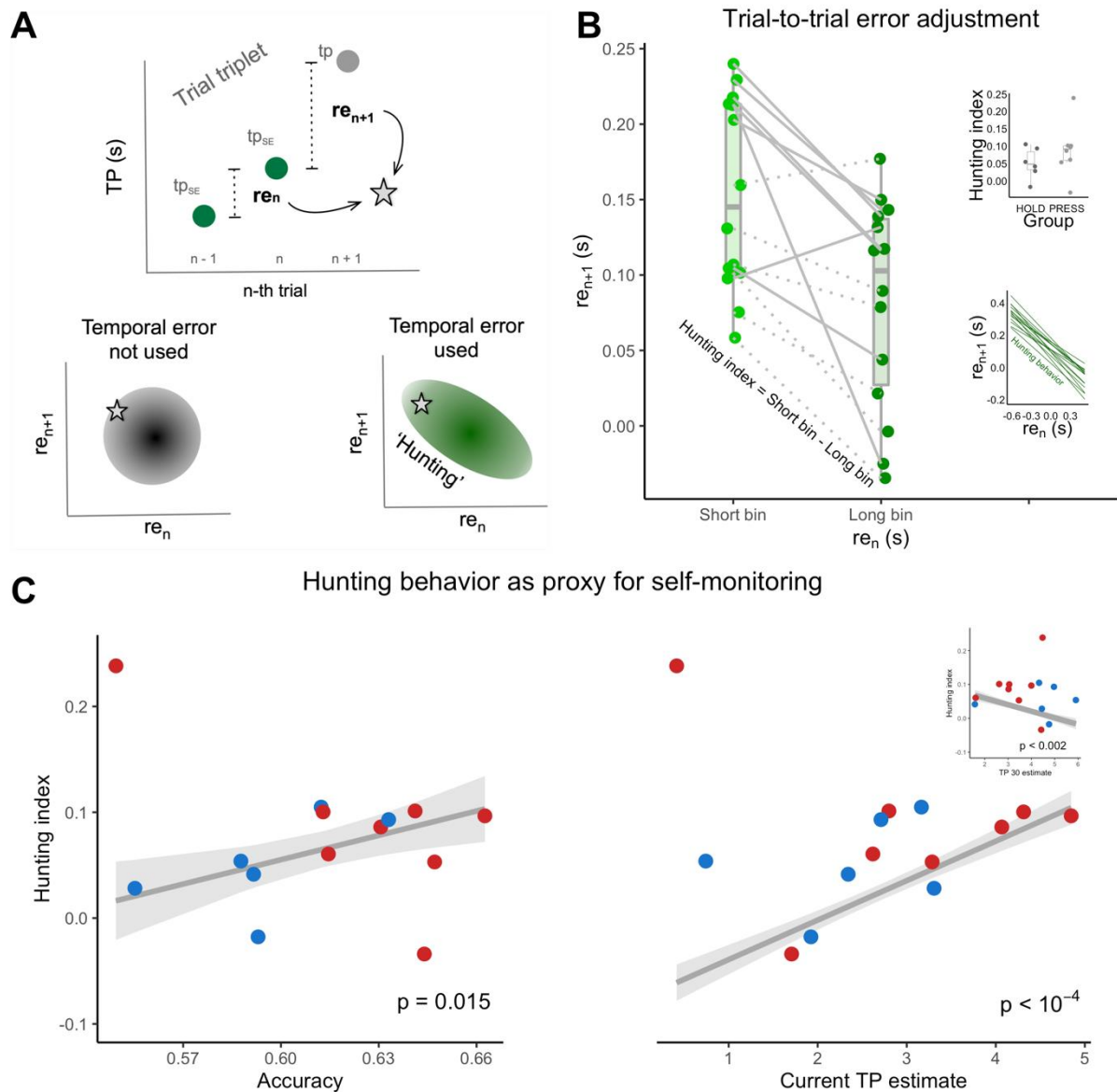


Figure 4. Inferred timing errors guide future behavior.

(A) The error estimation hypothesis predicts adaptation on the $n+1$ trial and so-called ‘hunting’ behavior. In top panel, we considered triplets of trials where the two first trials were 2p trials. Relative error in TP on n trial is calculated as the subtraction of TP during the second trial from TP during the first in a given triplet ($re_n = TP_n - TP_{n-1}$). Relative error in TP on $n+1$ trial is result of the subtraction of TP in the third trial from TP in the second trial in a given triplet ($re_{n+1} = TP_{n+1} - TP_n$). The bottom panels depict predictions in case when temporal errors are used or not used to guide behavior. If temporal error monitoring does not guide behavior no correlation between re_n and re_{n+1} is predicted. However, the hypothesis of an error monitoring predicts a negative association between re_n and re_{n+1} , which is depicted in the bottom right panel.

(B) re_n were categorized as short and long bins, based on re_n magnitude. Values of re_{n+1} are plotted against short and long re_n bins. Grey lines connect data points for individual rats. Dotted lines represent HOLD group and solid lines represent PRESS group. To compute an index of error adjustment (aka ‘hunting index’), we subtracted re_{n+1} of the long bin from that of the short bin. The values of hunting index for each rat are plotted in panel C along y axis.

Top inset plot: The values of hunting index plotted for both groups. No between-group difference was found ($t(12) = 0.40, p = 0.70$, t-test).

Bottom inset plot: Results of GLMM fit including current re_n as a predictor of re_{n+1} for each individual rat. Each line depicts a correlation slope for each individual rat. This negative relationship between re_n and re_{n+1} was

confirmed with linear mixed regression ($\beta = -0.36$, $t(12) = -5.70$, $p < 10^{-3}$, GLMM), in line with analysis in the main plot in figure 4B.

(C) The blue (HOLD group) and red data points (PRESS group) display the hunting index for each rat plotted against overall choice accuracy on test-trials (left panel) and values of current TP (right panel) and TP history (inset plot in the right panel) estimated from the same model fit. The green lines depict resulting fits of robust regression model. The shaded grey area represents confidence intervals.

1 Discussion

2
3 Although primates and rodents can report their confidence in perceptual tasks (e.g., Dehaene
4 et al., 2017; Kepecs et al., 2008; Fleming et al., 2010; Miyamoto et al., 2018), whether rodents
5 can monitor the errors of self-generated behavior, such as the production of a time interval,
6 was not known. Our results provide evidence for self-monitoring of temporal errors in rats.
7 During timing behavior and its evaluation, rats displayed behavioral characteristics suggesting
8 an online assessment of their temporal errors in line with the idea that rats represent rich
9 experiential variables. Previous studies suggested that rats may take into account their internal
10 temporal uncertainty during timing behavior, but an alternative explanation for a behavior
11 resembling error monitoring was offered for all the previous studies (for review Balci et al.,
12 2011). For example, Foote and Crystal (2007) trained rats to discriminate short and long
13 stimulus durations; when rats were faced with trials close to discrimination boundary, they
14 chose smaller but certain reward, without taking the risk of choosing short, or long, and
15 receiving no reward. The alternative explanation is that rats learned differential reinforcement
16 for different durations (Jozefowicz et al., 2009), putting in question monitoring of temporal
17 errors. However, if animals were responding according to two different memory
18 representations in our time production task, a bimodal TP distribution would have been
19 expected, which we did not observe in the current study.

20
21 The paradigm overcome the previous difficulties by employing time production instead of
22 stimulus duration discrimination. By adapting timing thresholds individually for each rat, we
23 forced the animals to remain close to their individual limits of time discrimination. Additionally,
24 by designing a novel way to report temporal errors, we can avoid relying on the whole
25 distribution of responses, which is an indirect means to infer the plausibility of monitoring of
26 internal uncertainty (Balci et al. 2009; Yi & Dudman, 2013). Instead, rats reported estimated
27 errors in their timing behavior on a trial-by-trial basis to maximize reward. Their behavior was
28 based on both the mean and precision of their representation of the elapsed interval.
29 Remarkably, the rats showed the ability to track their error on the current trial, showing that
30 rats keep track of the internal variables on which decisions were based, and of the relation of
31 those variables to the target value. Along with tracking their error on the current trial, they
32 keep history of recent reinforcements to maximize the amount of reward in a given amount of
33 time. It suggests that, in addition to their capacity to store in memory multiple parameters of
34 their behavior (Kheifets et al., 2017), rats have an exquisite ability to monitor their self-
35 generated behavior. Furthermore, the association of test-trial accuracy and size of the TP
36 correction between consecutive trials suggests that rats can use estimated errors to guide
37 future behavior, supporting a functional role of error monitoring in guiding adaptive behavior.

38
39 One limitation of the current study is the usage of just one very specific reward assignment
40 rule. On one hand, it forced the rats to be more precise, as TPs close to the objective threshold
41 were rewarded with two pellets. On the other hand, the distribution had to be titrated in
42 proportion to the reward size. Thus, the question remains of how rats would perform with
43 different reward assignment rules. The question is important as it touches on the relation
44 between levels of temporal uncertainty and ability to report temporal errors. Investigating
45 different levels of precision in the future will allow understanding the properties of
46 representations that rats use to keep track of time. Modification of the reward assignment rule

1 should also allow to investigate whether rodents possess the ability to monitor the sign of
2 temporal errors as humans (Akdoğan & Balci 2017; Kononowicz et al., 2018).

3

4 Our finding of error monitoring of timing behavior in rats is markedly similar to recent findings
5 in humans, where participants were able to report signed magnitude of their temporal errors
6 (Akdoğan & Balci 2017; Kononowicz et al., 2018). Although we do not claim that rats and
7 humans use the same cognitive machinery for monitoring of temporal errors, our results
8 indicate that rats use basic computations allowing error monitoring, whereby the monitoring
9 process actively infers the state of an 'internal clock'. Ultimately, these results deepen our
10 understanding of error monitoring abilities in rodents, and demonstrate a richness of
11 representation of elapsed time that goes beyond trial-and-error strategy in interval timing.
12 Together, thanks to our novel way to investigate animal cognition, the present findings show
13 that monitoring of internal uncertainty is not a privilege of primates. The current study
14 contributes to ongoing discussion on self-monitoring (Dehaene et al., 2017).

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1 **Methods**

3 *Subjects*

5 The subjects were male Sprague-Dawley rats (N=16; Envigo, France). They were 3 months old
6 at the beginning of the experiments. The rats were housed in groups of 4, and kept under a 12
7 h–12 h light/dark cycle. The experiments were performed during the light cycle. After one week
8 of acclimation to the vivarium with ad libitum food and water access, rats were food restricted
9 such that their weight reached and were maintained at 85% of their free-fed weight. All rats
10 were handled, weighed and fed daily until the end of the experiment. For all rats, two
11 experimental sessions were scheduled per day. The first and the second session of the day was
12 separated by approximately 3 hours during which rats returned to home cages with water
13 access. The experiment was carried out in accordance with the guidelines established by the
14 European Communities Council Directive (2010/63/EU) for compliance and use of laboratory
15 animals, and approved by the French Ministry of Research and the French National Ethical
16 Committee (2013/6).

18 *Apparatus*

20 The experimental setup was built using the Habitest Modular System (Coulbourn Instruments,
21 Allentown, PA, USA) with an operant box (Rat Test Cage, H10-11R-TC) placed in an isolation
22 cubicle (H10-24A). Figure 1 depicts the spatial arrangement of the behavioral box. On the left
23 wall, a retractable lever (H23-17RC) was placed between two reward ports (H14-01R), each
24 connected to a feeder (H14-23R) delivering grain-based pellets (45 mg, Phymep, Dustless
25 Precision Pellets, Paris, FR) and with photocell sensors (H20-94) to measure port entries. Lever
26 was separated from feeders by 7 cm and was placed 6.5 cm above the floor grid. Reward ports
27 contained an LED to serve as a reward cue after each successful time production. A red house-
28 light (H11-01R-LED) and a speaker (H12-01R) were placed on the right wall. The system was
29 controlled and data collected using Graphic State 4 software. The data were converted to text
30 files and analyzed using custom written R code.

32 *Procedure: pretraining*

34 The pretraining followed several steps. The first step was the feeder training (2 sessions) which
35 consisted in familiarizing rats with the reward ports, and the pairing of the pellet drop with the
36 onset of the reward-port light. A trial started after an inter-trial interval (ITI), randomly chosen
37 from 10 to 15 s (in steps of 1s), with a pellet drop that was simultaneous with the onset of the
38 light in the reward port. The light stayed on for up to 2 s unless the pellet had been picked-up.
39 Rats had 7 s to pick up the pellet. The next trial started when a pellet was collected or when 7
40 s had elapsed. The session ended when rats collected 40 pellets. The side of the reward delivery
41 was pseudo-randomized.

43 In the second pretraining step (port-light training, 10 sessions), the rats were required to nose-
44 poke in the reward port in order to receive the reward. The maximal time for which the port-
45 light cue would stay on was set to 5 s. All other aspects of the task remained unchanged. When
46 all rats successfully collected rewards on more than 80 % of trials in two consecutive sessions,
47 we moved to the third step.

1
2 In the third step (lever-press training, 3 sessions), the rats were required to press a lever in
3 order to activate the light cue. The trial started with the lever presentation, that the rats had
4 to press for turning on a port-light cue (randomly chosen to be the left or the right side) waiting
5 for the rat to poke in for reward delivery. The lever was retracted after a lever press was made
6 or 5 s had elapsed, and a new ITI started. Rats could earn 50 pellets in one session, otherwise
7 the session ended after 30 min. All rats reached a criterion of 80 % rewarded trials in two
8 consecutive sessions.

9 10 *Duration and precision training*

11
12 Two groups of rats were formed, corresponding to two different ways of producing durations.
13 One group of rats (N=8; HOLD group) was trained to hold the lever down for a required time of
14 target duration. The lever press and the lever release served as onset and offset times for the
15 produced duration, respectively. The second group of rats (N=8; PRESS group) was trained to
16 produce a duration spaced between two lever presses. The first lever press and the second
17 lever press served as the onset and the offset times, respectively. Generation of another press
18 by PRESS group likely involves more degrees of freedom in the rat's motor routine. Slightly
19 more complex motor pattern likely translated to difference in precision of TP (Fig. 1). Four
20 operant boxes were used to train the rats. Two rats of the PRESS and of the HOLD groups were
21 assigned to each operant box. Two rats of each home cage were assigned to PRESS and two
22 were assigned to HOLD to counterbalance for any 'home cage' effects.

23
24 We refer to the time interval that the rat produced, on any given trial, as Time Production (TP).
25 To train the rats to produce a duration of 3.2 s, which we refer to as the target duration (T), we
26 followed the procedure used by Platt et al. (1973). We started with T of 0.4 s, for which rats
27 obtained access to the reward only if they produced a duration of at least 0.4 s. To train the
28 rats on longer durations, we increased progressively T following logarithmically spaced targets
29 between 0.4 s and 3.2 s (T: 0.4, 0.61, 0.92, 1.39, 2.11, and 3.2 s). For each rat, and in each
30 session, a density function was calculated for the TP distribution, as well as the associated
31 proportion of the area under the curve that exceeded the criterion T. A longer T was introduced
32 to all rats when 80 % of the area under the curve exceeded the T criterion on two consecutive
33 sessions. However, computation of thresholds in the remaining parts of training was performed
34 individually.

35
36 On any given trial of duration and precision training trial (Supp. Fig. S1) the lever was inserted
37 after an ITI of 4 to 8 s (in temporal increments of 1 s). The rats had unlimited time to initiate
38 their interval production by pressing the lever. When the TP (holding or pressing twice,
39 depending on the group assignment) was too short ($TP < 3.2$ s), the lever was retracted and the
40 trial restarted with the insertion of the lever after a random ITI. After the rewarded trials (3.2 s
41 $< TP < 2 * \sigma(TP)$), rats had between 4 s to 8 s to collect their reward, after which, the lever was
42 presented again. The ITI was adjusted by the sound duration, resulting in ITI values ranging
43 from 3 s to 7 s. This trial structure remained unchanged until the end of the experiment.

44
45 Once all subjects achieved the T criterion for correct performance on the final T (3.2 s), a bound
46 on longer durations was introduced that equated $2 * \sigma_{TP}$, meaning that rats were not reinforced
47 in trials in which their TP exceeded two standard deviations away from the mean TP calculated

1 over the two previous sessions (σ_{TP}). This procedure intended to force the animal to be precise
2 in their TP. To signal to the rats that a TP was too long, a tone (4 kHz, 1s, 75 dB) was played
3 after the TP was terminated. The sound was incorporated to distinguish the too-long no-reward
4 trials from the too-short no-reward trials. During the precision training, every 2 sessions the
5 threshold for too-long TP was recomputed on a per rat basis. We observed that TP precision
6 increased in the course of precision training, however we did not define a strict stop-rule
7 criterion as a changed payoff in the next training step could have caused further increase in TP
8 precision. Within one session, the rats could obtain up to 100 pellets. The session was limited
9 to 45 minutes. Rats adjusted their behavior in response to the sound signal by producing a
10 narrower TP distribution, rendering them more precise in their TP.

11
12 During the duration training, the port-light cue always correctly indicated the reward-port in
13 which a reward was available. The reward port was randomly chosen with 50 % chance. All rats
14 chose the cued port first with accuracy above 95 %. The duration training took 34 sessions; the
15 precision training took 12 sessions.

16 17 *Error monitoring training*

18
19 We refer to this part of training as error monitoring training, which took 36 sessions. In this
20 phase, the rats learned to assign a reward size as a function of their error size in TP. To assign
21 reward size to TP errors, we estimated a threshold (Θ) based on the individual TP distribution.
22 Figure 1C depicts a hypothetical distribution of TP for a given animal. More accurate TP (which
23 we name TP_{SE} for TP Small Error), between T and Θ , were rewarded with 2 pellets in one port
24 (Fig. 1C, green area). The less accurate TP (which we refer to as TP_{LE} for TP Large Error),
25 between Θ and $2*\sigma(TP)$, were rewarded with 1 pellet in the other port (Fig. 1C orange area).
26 Θ was estimated as a point dividing the green and orange areas with 1 to 2 ratio (Fig. 1C). The
27 first threshold (Θ) to separate green and orange areas was computed based on the
28 performance of the animals in the two last sessions of precision training. The optimal ratio of
29 2p to 1p trials was 0.5, calculated as the proportion of TP_{SE} (2p) and TP_{LE} (1p) trials. That ratio
30 guaranteed equal number of pellets delivered in both ports. Thresholds Θ were computed for
31 each animal individually. Θ was updated when rats deviated from optimal ratio by factor of 3,
32 meaning that when the lower (0.16) or upper (1.5) bound were exceeded. The individual
33 thresholds were recalculated when the update bounds were exceeded on two consecutive
34 sessions.

35
36 The contingencies assigning TP length to a reward port are depicted in Figure 1CD. Specifically,
37 on a given trial, after TP generation, if TP fell between T and $2*\sigma(TP)$, either the left port or the
38 right port was lit, chosen randomly. For TP_{SE} trials (green area) animals received 2 pellets in the
39 one port ('2p port') or 0 pellet in the other port ('1p port'). We refer to trials rewarded with 2
40 pellets and 0 pellet as TP_{SE-2P} and TP_{SE-0P} , respectively. Generation of TP_{SE} on a given trial
41 resulted in a 50% chance of receiving a reward as TP_{SE-2P} or TP_{SE-0P} , as indicated by the arrows
42 above pointing to the 2p and 1p port. For less accurate TPs that landed in the orange area
43 animals received 1 pellet in the 1p port or 0 pellet in the 2p port. We refer to TP_{LE} trials that
44 were reinforced with 1 pellet and 0 pellet as TP_{LE-1P} and TP_{LE-0P} , respectively. The assignment of
45 TP_{LE-1P} and TP_{SE-2P} to the left and right port was counterbalanced across animals. Subject
46 entered the lit port on 95% of test-trials on average. Entering the unlit port caused trials
47 termination.

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Error monitoring test sessions

To test whether animals were able to report temporal errors, we used the same trial structure as in error monitoring training, but added choice trials (Fig. 1C). We used the same paradigm as in the error monitoring training sessions on 80 % of trials. On the remaining 20 % of trials, we introduced test-trials in which both ports were lit up, giving the animal an opportunity to choose according to the rule described above. Thus, in those test-trials, the rats were offered the possibility to get a reward in either port, with a reward size (0 vs 1 vs 2 pellets) depending on their TP. To maximize the reward rate, the animals should choose in line with the accuracy of time production, categorized as TP_{SE} or TP_{LE}. Choosing TP_{SE-2p} on TP_{SE} and TP_{LE-1p} on TP_{LE} trials would be suggestive of error monitoring abilities. Within one session rats could obtain up to 130 pellets. Session time was limited to 65 minutes. In total, the rats performed 40 error monitoring test-sessions.

Data processing

All analyses used custom-written scripts in R (3.6.1; "Action of the Toes"; R Core Team; 2008). Data sets of individual sessions were removed only if equipment malfunctioned, or when a small number of test-trials was obtained in one of the ports (< 5). In total, we removed 50 individual data sets (per rat and per session) out of 640 data sets of all test sessions (equivalent to 8%).

Statistical analysis

To account for sample dependency, we used linear mixed-effects models (e.g., Gelman & Hill, 2007; Pinheiro & Bates, 2000) as implemented in R package *lme4* (v.1.1-21), that is, for multiple per-animal observations across sessions. Linear mixed-effects models (LMM) are regression models that model the data by taking into consideration multiple levels. Overall, linear mixed-effect model can be expressed as (Laird & Ware, 1982):

$$(1) y_i = X_i\beta + Z_i b_i + \varepsilon_i, i=1, \dots, M, b_i \sim N(0, \Sigma), \varepsilon_i \sim N(0, \sigma^2 I),$$

where y_i is a response vector for the i -th grouping, β is a vector of fixed effects, ε_i reflects error term, b_i is a vector of random effects, X_i and Z_i are matrices reflecting fixed and random effect design. Perhaps the most straightforward and intuitive distinction between fixed and random effects posits that fixed effects are assumed to be constant over experiments, while random effects are a random subset of the levels in the underlying population (Barr et al., 2013).

Animals and sessions were random effects in the model and were allowed to vary in their intercept. P values were calculated based on a Type 3 ANOVA with Satterthwaite approximation of degrees of freedom, using the *lmerTest* package in R (Kuznetsova, Brockhoff, & Christensen, 2017). The mixed-effects model approach was combined with model comparisons that allow for selecting the best fitting model in a systematic manner. Model comparisons were performed based on Akaike Information Criterion (AIC).

As we collected 40 test sessions for each rat, we considered the option to add a nested random effect structure, reflecting that each rat could perform slightly differently on each session. To select the random effect structure, we fitted a model including only the intercept term,

1 comparing different random effect structures using Chi-square test and AIC. We started with a
2 model containing only the intercept term for different rats. Model comparison showed that the
3 addition of an intercept term for each session, nested within a rat, was justified ($\Delta\text{AIC} = 3164$,
4 $\chi^2 = 3262$, $P = 10^{-15}$). The addition of a random slope effect for each predictor was also justified
5 when compared against the model with random intercept per rat and per session ($\Delta\text{AIC} = 2290$,
6 $\chi^2 = 2300$, $P = 10^{-15}$). The random slope effects reflected the fact that each rat could perform
7 differently. The random effects definition remained unchanged for all assessed models.

8 9 Time production analysis (related to Fig. 1B, Supp. Fig. 3)

10
11 The mean (μ) and standard deviation (σ) of TP were calculated across sessions and across rats.
12 To remove the left-tail reflecting impulsive responses and motor errors, we analyzed TP longer
13 than 2 s. On average, each rat produced 218 trials per session excluding trials below 2 s, and
14 223 including trials of all durations. To assess whether the standard deviation of TP scaled with
15 the mean of TP, we performed LMM, which included rats as random effect, of the following
16 form:

$$17 \quad (2) \quad y_{sr} = \beta_0 + \beta_1 \mu TP_{sr} + b_{0r} + \varepsilon_{tsr}, \quad b_{0r} \sim N(0, \sigma_0^2), \quad \varepsilon_{tsr} \sim N(0, \sigma^2).$$

18 Indices t, s, and r stand for trial, session, and rat, respectively. μTP_{sr} indicates the mean time
19 production calculated per session and per trial, which was included as a fixed effect as indicated
20 by the β_1 coefficient. b_{0r} stands for the random effect of rat. To compare differences between
21 the two groups of rats, we included session as a random effect (Supp Mat. S3).

22 23 Reaction time analyses (related to Fig. S4)

24
25 To assess whether rats expressed confidence in their choices, differences in RT for rewarded
26 and unrewarded trials, for the 1 pellet and 2 pellet ports (Supp. Fig. 4A; RT $TP_{SE-1p} - RT_{LE-0p}$
27 (dark red)); RT $TP_{LE-2p} - RT_{SE-0p}$ (green)) were calculated. Differences in mean RT were
28 calculated for each session and each rat. Therefore, the linear mixed model included a nested
29 intercept term of session, which was allowed to vary within each rat.

30
31 To test whether rats expressed choice behavior on test-trials in which both ports were lit, RT
32 were also averaged on a per session and per rat basis (Supp. Fig. 4B). Test-trials were contrasted
33 against training-trials. LMM was formulated similarly to formula 2, including a random effect of
34 rat.

35 36 Choice accuracy on test-trials (related to Fig. 2)

37
38 Overall we collected 21129 test trials. Average number of test-trial per rat, per session was 37.9
39 (Supp. Fig. 10). Individual accuracies were tested against chance level using Wilcoxon test,
40 separately for each rat. Samples were mean accuracy in a session. The exact results are
41 presented in the Supplementary Table 1. The last column of Supplementary Table 1 provides
42 information in how many session accuracy of an individual rat was higher than 55%.
43 Additionally, Supp. Fig. 11 displays 2p/1p ratio obtained per session, per rat. The data displayed
44 in Supp. Fig. 10 and Supp. Fig. 11 were used to analyze the association between accuracy and
45 pellet ratio in paragraph: "Rats choose accurately on test-trials, expressing error monitoring".
46

1 To assess the difference in accuracy between PRESS and HOLD groups, the average
 2 accuracy was computed on a per session and per rat basis. The data were tested using LMM
 3 with a random intercept of session.

4
 5 Predicting choices based on TP (related to Fig. 2CDE)

6
 7 Accuracies for rat 1 and 2 in HOLD group were marginally significant, and they did not exhibit
 8 choice behavior on at least half of the sessions (Fig. 2A). Therefore, they were excluded from
 9 the single-trial analyses.

10 A simplified generalized linear model (GLM) was fit to illustrate the principle of
 11 performed analyses. Rat (nr 7, PRESS group, session 32) choices from a single session (2p port
 12 vs 1p port choices) were predicted using TP from the same trial. That GLM had the following
 13 form:

14 (3) $\log\left(\frac{P(1p)}{P(2p)}\right)_t = \beta_0 + \beta_1 TP_t + \varepsilon_t, \varepsilon_t \sim N(0, \sigma^2),$

15 where TP_{nt} stands for TP on single trial.

16 Modified version LMM, that is generalized linear mixed model (GLMM), was used to
 17 model binary outcome variable (2p port vs 1p port choices) to determine whether TP predicts
 18 rats' choices. The most basic GLMM had the following form:

19 (4) $\log\left(\frac{P(1p)}{P(2p)}\right)_{tsr} = \beta_0 + \beta_1 TP_{tsr} + b_{0r} + b_{1sr} + \varepsilon_{tsr},$

20 $b_{0r} \sim N(0, \sigma_0^2), b_{1sr} \sim N(0, \sigma_1^2), \varepsilon_{tsr} \sim N(0, \sigma^2)$

21 The log-odds of rats' choices were modeled as a function of time production (TP), expressed by
 22 TP rat. $b_{0r} + b_{1sr}$ express random intercept of rat and session, with session nested within a rat.
 23 Nested random intercepts of session within rat was kept for remaining model fits. The model
 24 was fit using 19,512 samples of test-trials.

25
 26 Predicting choices based on TP and reward history (related to Fig. 3, Supp Fig. 5, 6, 7)

27
 28 To investigate whether rats used sources of information other than current trial TP error to
 29 choose accurately on test-trials, we first fitted a model incorporating lagged rewards and TP on
 30 previous trials (Supp. Fig. 5A, 5B, respectively). We used current TP and fifteen other predictors
 31 (different lags) which were reward size (Reward History, RH) or TP vectors lagged by n trials (n
 32 = {1:15}). We used a similar approach, as introduced in the previous paragraph with several
 33 extensions. The model of the following form:

34 (5) $\log\left(\frac{P(1p)}{P(2p)}\right) = \beta_0 + \beta_1 TP_{tsr} + \beta_2 RH_{1tsr} + \beta_3 RH_{2tsr} + \beta_4 RH_{3tsr} + \dots + \beta_{16} RH_{17tsr} + b_{0r} + b_{1sr} + \varepsilon_{tsr}, b_{0r} \sim$

35 $N(0, \sigma_0^2), b_{1sr} \sim N(0, \sigma_1^2), \varepsilon_{tsr} \sim N(0, \sigma^2),$

36 was enhanced with a fixed effect of reward history (RH_n), where n stands for the trial lag. The
 37 model where TP was included instead of RH (Supp. Fig. 5B) was of the same form. Both models
 38 were fit using 19,309 samples of test-trials.

39
 40 To investigate cumulative effects of reward history, we calculated mean μRH_n across n trials.
 41 One individual trace of nonstationary TP was visualized in Fig. 3A. All RH traces that were used
 42 in this analysis were visualized in Supp. Fig. 7. Using these predictors, we fitted a model of the
 43 following form:

44 (6) $\log\left(\frac{P(1p)}{P(2p)}\right) = \beta_0 + \beta_1 TP_{tsr} + \beta_2 \mu RW_{10tsr} + \beta_3 \mu RW_{20tsr} + \beta_4 \mu RW_{30tsr} +$

45 $b_{0r} + b_{1sr} + b_{2sr} TP_r + b_{3r} \mu RW_{10r} + b_{4r} \mu RW_{20r} + b_{5r} \mu RW_{30r} + \varepsilon_{tsr},$

46 $b_{0r} \sim N(0, \sigma_0^2), b_{1sr} \sim N(0, \sigma_1^2), b_{2sr} \sim N(0, \sigma_2^2), b_{3sr} \sim N(0, \sigma_3^2), b_{4sr} \sim N(0, \sigma_4^2),$

1 $b_{5sr} \sim N(0, \sigma_5^2), \epsilon_{tsr} \sim N(0, \sigma^2),$

2 where $\beta_1 TP_{tsr}$ express a fixed effect of TP, and $\beta \mu RW_{ntsrsr}$ express a fixed effect of cumulative
3 reward in 1p and 2p ports in n last trials. In addition to nested session by rat random intercepts,
4 as in the previous models, we added a random effect of slope for each rat ($b_r \mu RW_{nr}$). A model
5 of the same structure was fit for μTP_n cumulative TP history. Both models were fit using 16,973
6 samples of test-trials. The difference of 2,539 trials, as compared to initial model, was due to
7 averaging of previous trial, causing removal of initial 30 trials of each session.

8

9 *Predicting relative errors based on error monitoring accuracy (related to Fig. 4)*

10 To investigate whether rats adjust their errors between trials we identified triplets of trials
11 where the two first trials were accurate trials rewarded with 2 pellets. In total, we identified
12 2750 such triplets from all rats (Fig. 4B).

13

14 We observed outliers in Fig. 4C, which violate the normality assumption of a linear regression.
15 Therefore, we used a robust linear model that attempts to minimize the influence of outlier
16 observations without removing them from a dataset. Using Robust and Efficient Weighted
17 Least Squares estimator (Gervini & Yohai, 2002), the least square weights were adaptively
18 estimated using the empirical distribution of residuals. As such, robust methods are less
19 sensitive to a non-normal distribution. All models, in this section, were implemented using
20 'robust' R package (v0.5, Wang et al., 2020). The fitted model predicted hunting index with test-
21 trial accuracy (Fig. 4B). To disentangle the effect of different contributions of test-trial accuracy
22 to hunting index, we used individual coefficient for each rat, expressing current trial
23 contributions and previous trials contributions. Thus, we used parameters of fitted GLMM as
24 described in the Equation 6, however just with two terms: $\beta_1 TP_{tsr}$ and $\beta_2 \mu TP_{30tsr}$. We retrieved
25 the coefficient for each rat and used them as predictors of hunting index in the second fitted
26 robust regression (Fig. 4C).

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9

10

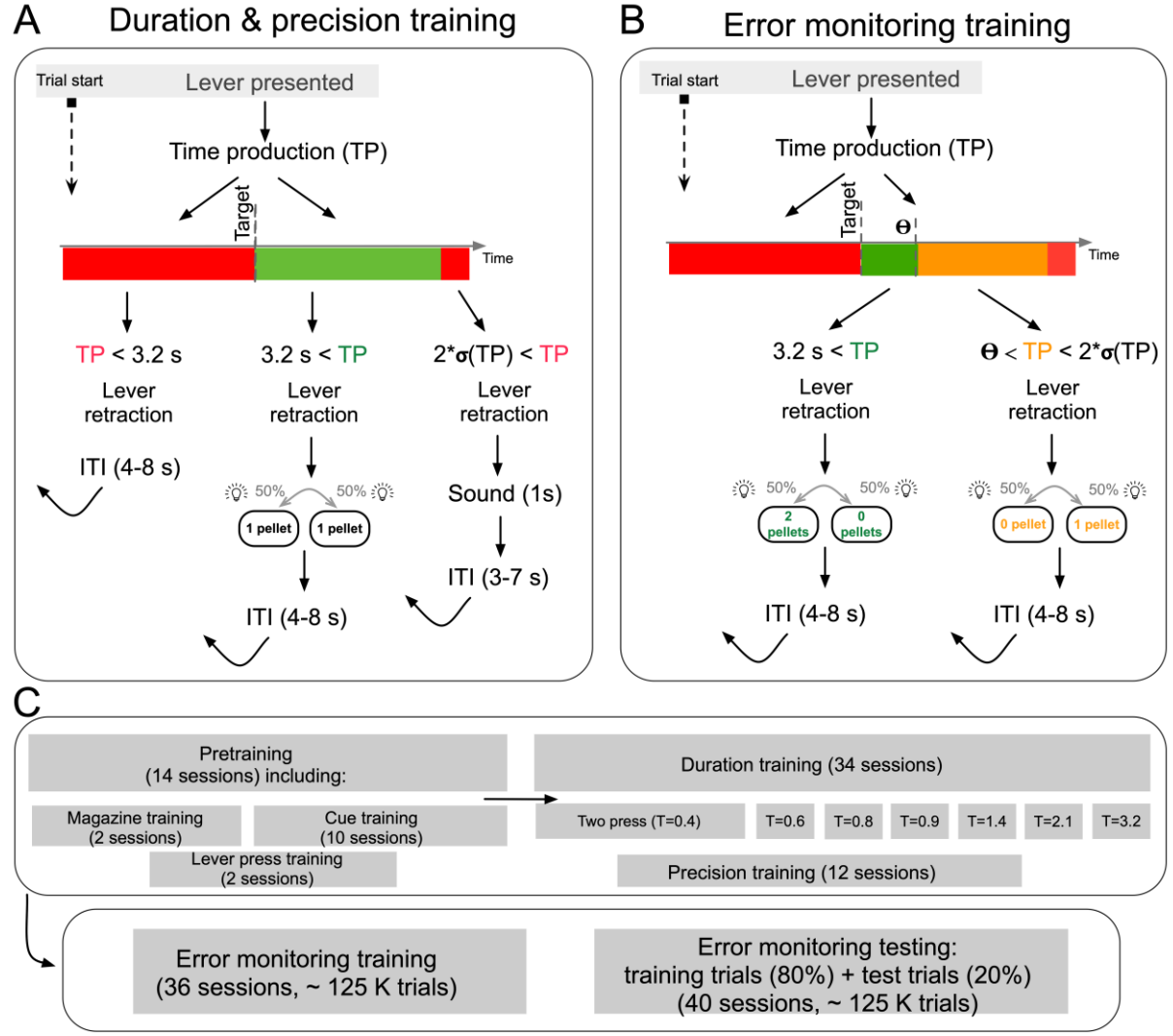
11 **Funding**

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13 ANR-TimeMemory to VD and VvW.
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Supplementary materials and figures

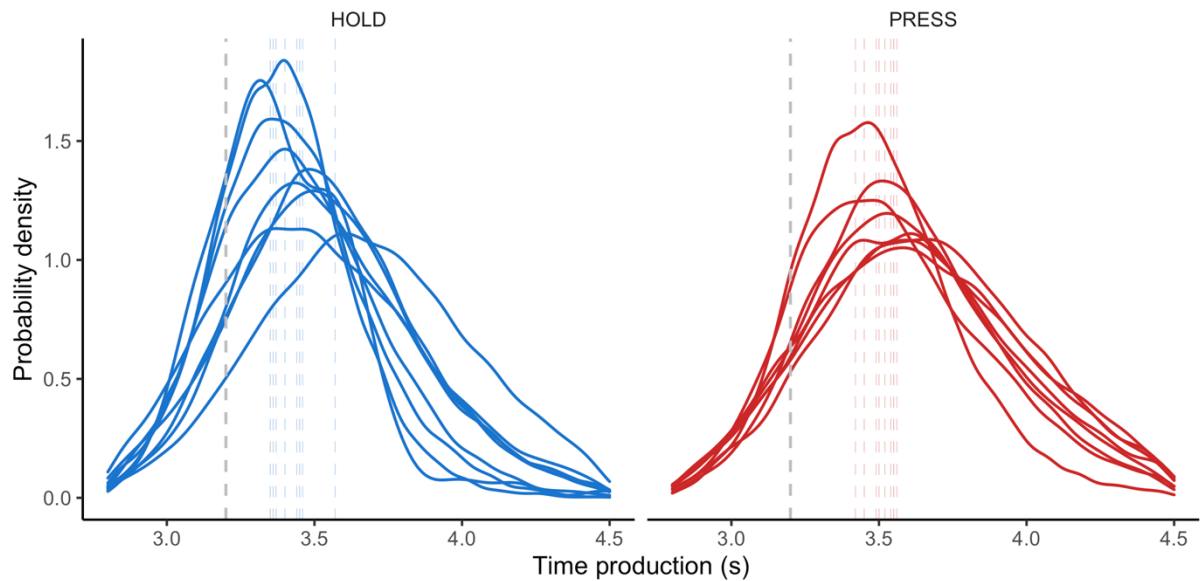
S1. Schematic of a trial structure during training



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Supplementary Figure 1. Trial structure during training. (A) Schematic of a trial structure on duration and precision training trials. Task events are depicted in sequence from the top to bottom. They differ along the TP-axis (color bar with red, green, and orange colors) and show different scenarios, in single trials, that were determined by rats' performance on TP. An inter-trial-interval (ITI) was the last event in a single trial sequence. See Methods: *Duration and precision* for further explanation. (B) Schematic of a trial structure on error monitoring training trials. See Methods: *Error monitoring training* for further explanation. (C) Schematic of pretraining and training procedure.

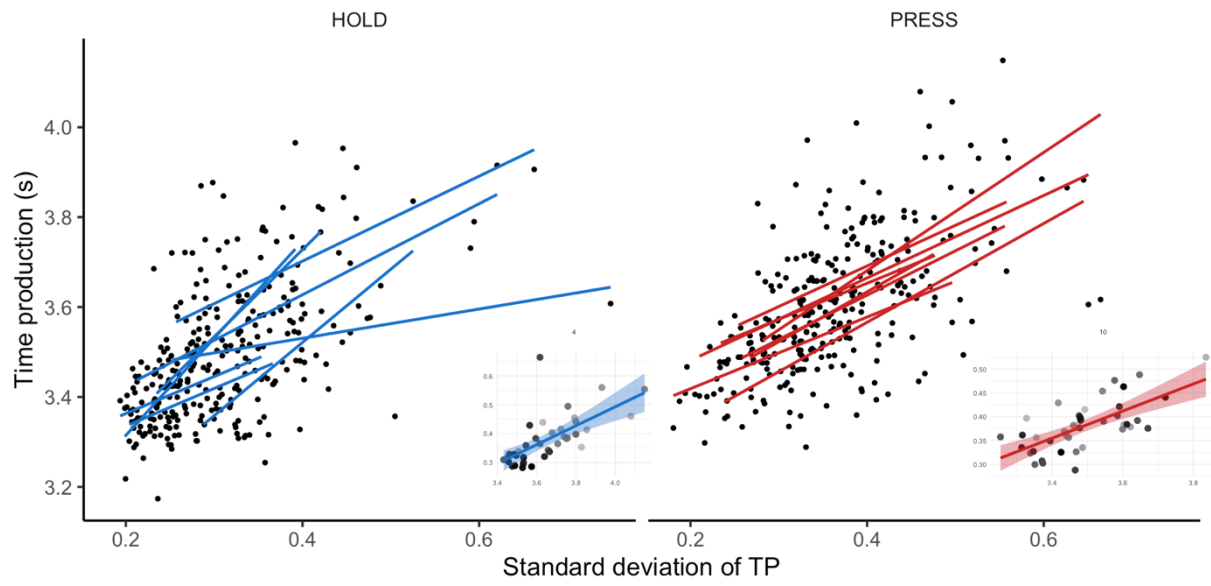
1 **S2. Time Production distributions for HOLD and PRESS groups**



2
3 **Supplementary Figure 2.** Time Production distributions for HOLD and PRESS groups displayed
4 in Fig. 1. Premature, impulsive responses were removed from the plot to accentuate
5 performance of interest around 3.2 s target duration.
6
7

8 **S3. Performance in Time Production differs between HOLD and PRESS groups (related to figure**
9 **1B)**

10 In the time production task (Fig. 1), animals had to produce time intervals by making two
11 presses spaced by the minimum amount of time (PRESS) or hold pressed a lever (HOLD) for a
12 minimum amount of time T ($T = 3.2s$) in order to get access to a reward. All rats were able to
13 produce the required time interval T , as TP distributions for all rats peaked after T (Fig. 2a). The
14 HOLD group was more accurate and precise than the PRESS group (Fig. 2B), which was evident
15 in a model comparing mean and standard deviation of TP between the two groups across all
16 sessions ($\beta = 0.11$, $t(551) = 8.86$, $SE = 0.012$ $p < 10^{-9}$; $\beta = 0.05$, $t(553) = 7.2$, $SE = 0.007$, $p < 10^{-9}$,
17 respectively). Despite this difference, but consistent with scalar variability in duration re-
18 production tasks (Jazayeri & Shadlen 2010), both groups showed increased variability with
19 increasing mean TP (Supp. Fig. 3). This was confirmed in a regression model predicting standard
20 deviation of TP with mean TP ($\beta = 0.28$, $t(586) = 15.4$, $SE = 0.18$, $p < 10^{-14}$). The addition of a
21 group factor to the model was not justified ($\Delta AIC = 0.3$, $p = 0.155$), suggesting that scalar
22 variability was preserved in both groups in a similar form (Supp. Fig. 3).

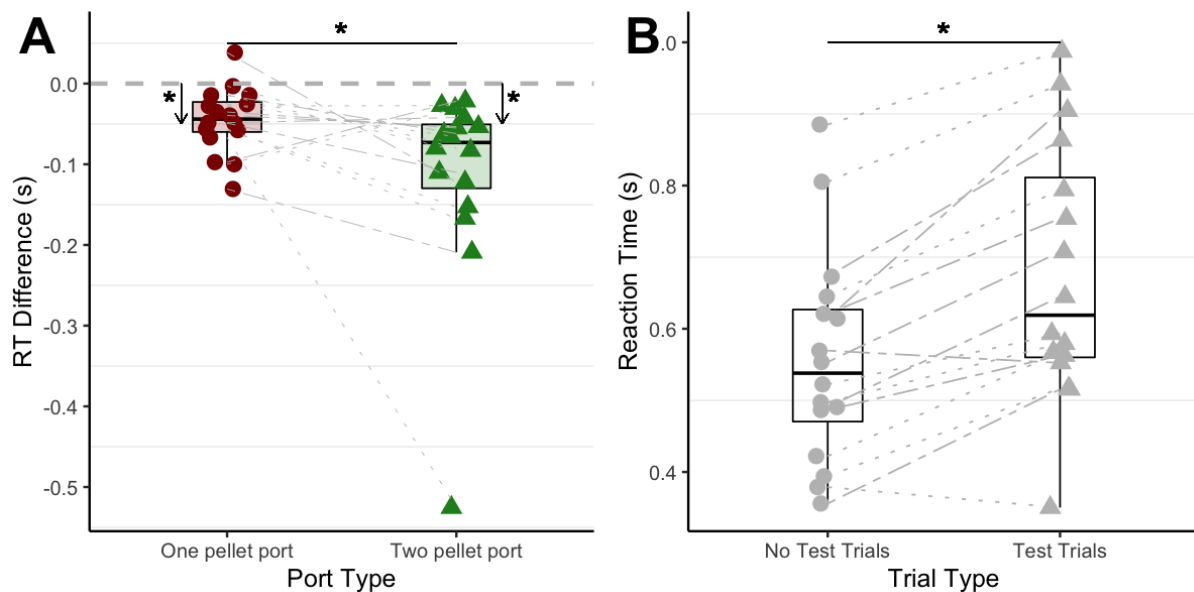


1
 2 **Supplementary Figure 3.** For each session and each rat, $\mu(\text{TP})$ is plotted against $\sigma(\text{TP})$ across
 3 sessions. Colored lines depict the regression fits for individual rats. Both panels contain inset
 4 plots showing a fit of one example rat.
 5
 6

1 **S4. RT reflects the prospect of larger reward**

2 As an indirect measure of temporal error monitoring, we analyzed reaction times (RT). We
3 hypothesized that RTs should be sensitive to reward anticipation based on reward prospect.

4 To assess the possibility of error monitoring in rats, the animals were trained to
5 associate TP accuracy (small error: TP_{SE} trials vs large error: TP_{LE} trials) with reward delivery
6 (TP_{SE-2p} and TP_{LE-1p} trials) or its absence (TP_{SE-0p} and TP_{LE-0p} trials) in one of the two ports. The
7 prospect of reward was indicated to animals, after TP was terminated, by a light cue in one of
8 the two ports. To check if reward will indeed be delivered on any given trial, animals were
9 required to first visit a port. Only upon the port visit did reward delivery or its absence become
10 apparent to the animal. From the animal's perspective, light cue to a particular port only
11 indicates the delivery side. However, if rats are sensitive to temporal errors, RTs should be
12 related to the accuracy of TPs, as classical work has shown that rats respond faster when
13 expecting larger rewards (Rosenbaum, 1951). Indeed, if rats produced accurate TP_{SE}, their RT
14 to the light cue in a port associated with 2 pellets should be more rapid than RTs following the
15 production of less accurate TP_{LE}, as 0 pellet would then be expected in that port. The opposite
16 dependence should hold for the other port (1 pellet port). This was evident in the relative RTs
17 comparing rewarded to unrewarded trials in a given port (Supp. Fig. 4A; RT TP_{LE-1p} - RT TP_{SE-0p}
18 (dark red); RT TP_{SE-2p} - RT TP_{LE-0p} (green), 1-pellet and 2-pellets port, respectively). The majority
19 of rats responded faster to a light cue on rewarded trials than on the non-rewarded trials in
20 each port. This effect was confirmed with a mixed model testing differences between the
21 rewarded and unrewarded trials. A significant intercept in the model indicated that the RT
22 difference was smaller than zero ($\beta = -0.018$ s) showing that RTs were faster on trials with the
23 reward prospect ($SE = 0.008$, $t(34) = -2.11$, $p = 0.043$). In line with the reward prospect
24 interpretation, rats responded also faster when reward prospect was larger (2p vs 1p), which
25 was evident as a significant factor of port type in the model (1p vs 2p; $\beta = -0.051$, $SE = 0.009$,
26 $t(1127) = -5.35$, $p < 10^{-6}$). The shortening of RT in anticipation of a larger reward prospect
27 strongly suggests that rats may monitor their temporal errors.
28



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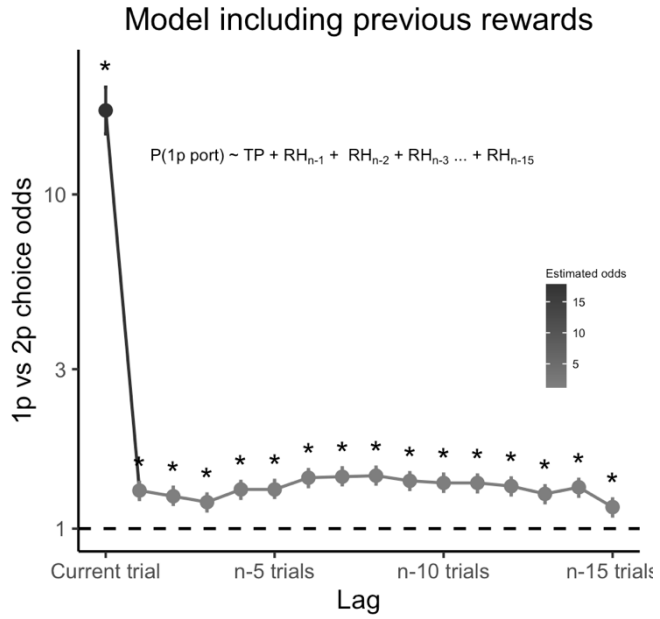
31 **Supplementary Figure 4.** Rats reacted faster to larger subjective internally-based reward
32 prospect.

1 (A) Data points from one column correspond to one rat. Each data point shows a reaction time
 2 difference between rewarded and unrewarded trials for 1p port (dark red; $TP_{LE-1p} - TP_{SE-0p}$) and
 3 2p port (green; $TP_{SE-2p} - TP_{LE-0p}$). A majority of rats reacted faster to rewarded trials as evident
 4 in negative values. Additionally, reaction time difference was larger for 2p trials.
 5

6 (B) RT on test-trials indicated choice behavior. Each individual data point shows a reaction time
 7 in training-trials (no choice) and test-trials (choice available). Rats showed longer RT during test-
 8 trials than during the training-trials ($\beta = 0.14$, $SE = 0.011$, $t(1163) = 9.54$, $p < 10^{-15}$), indicating
 9 expression of choice behavior as opposed to random responding.
 10

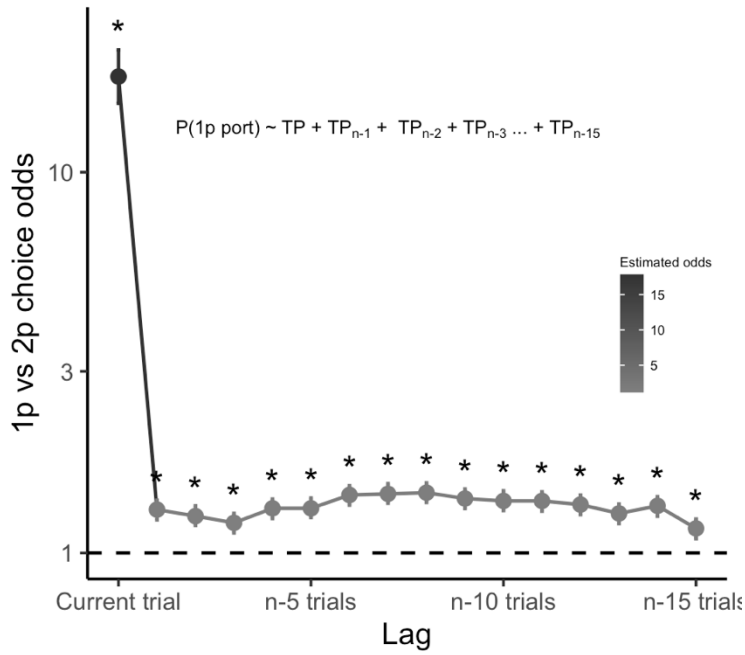
11 **55. RT reflects the prospect of larger reward**

12 To assess whether rats used previous trial outcomes, we fitted the model that included current
 13 TP and previous TPs, or previous rewards (RH) up to 15 trials back (n-15). Indeed, the estimated
 14 odds showed that previous rewards contributed to rats' choices (Supp Fig. 5a; n=0: $\beta = 2.87$, SE
 15 $= 0.083$, $z(18224) = 34.27$, $p < 10^{-15}$; n-1: $\beta = 0.25$, $SE = 0.031$, $z(18224) = 8.02$, $p < 10^{-14}$; see
 16 Supp Table 2), but with clear evidence for the strongest contribution of current TP. A similar
 17 pattern of results was obtained when current TPs were fitted together with previous TPs (Supp
 18 Fig. 4; n=0: $\beta = 2.82$, $z(18205) = 33.71$, $p < 10^{-15}$; n-1: $\beta = 0.51$, $z(18205) = 8.59$, $p < 10^{-15}$; see
 19 Supp Table 3).
 20

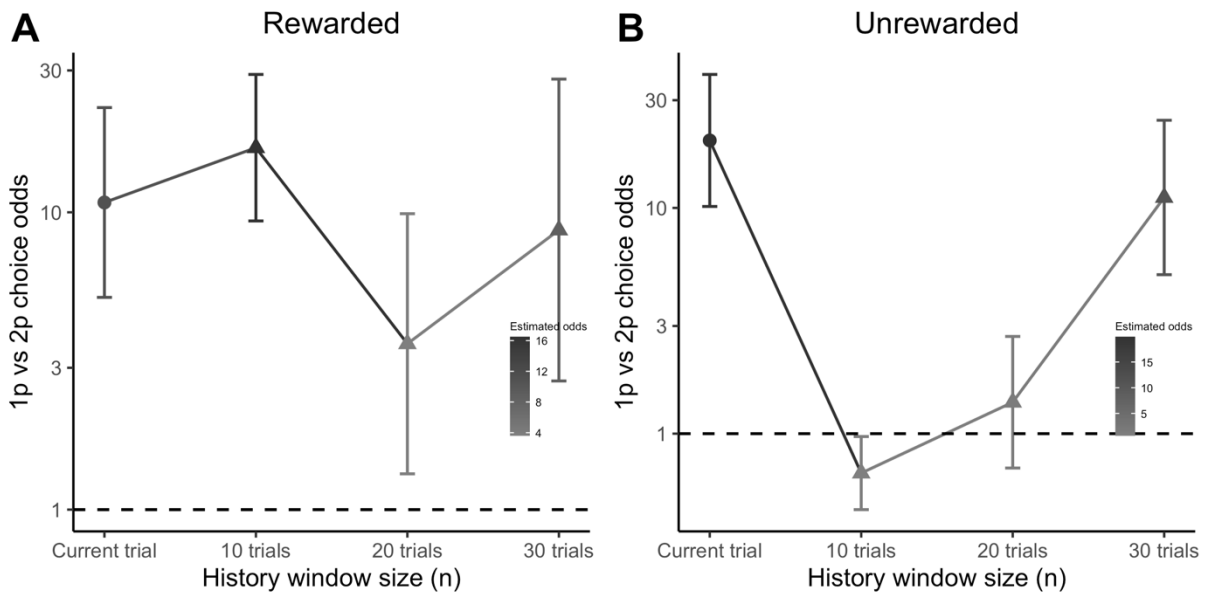


21 **Supplementary Figure 5A.** Results of GLMM fit including current TP and reward history (RH)
 22 incorporated as rewards received on up to 15 previous trials. The formula in the plot shows
 23 specification of fixed terms in the GLMM. Asterisks indicate significant terms. Error bars display
 24 confidence intervals of estimated effects.
 25
 26

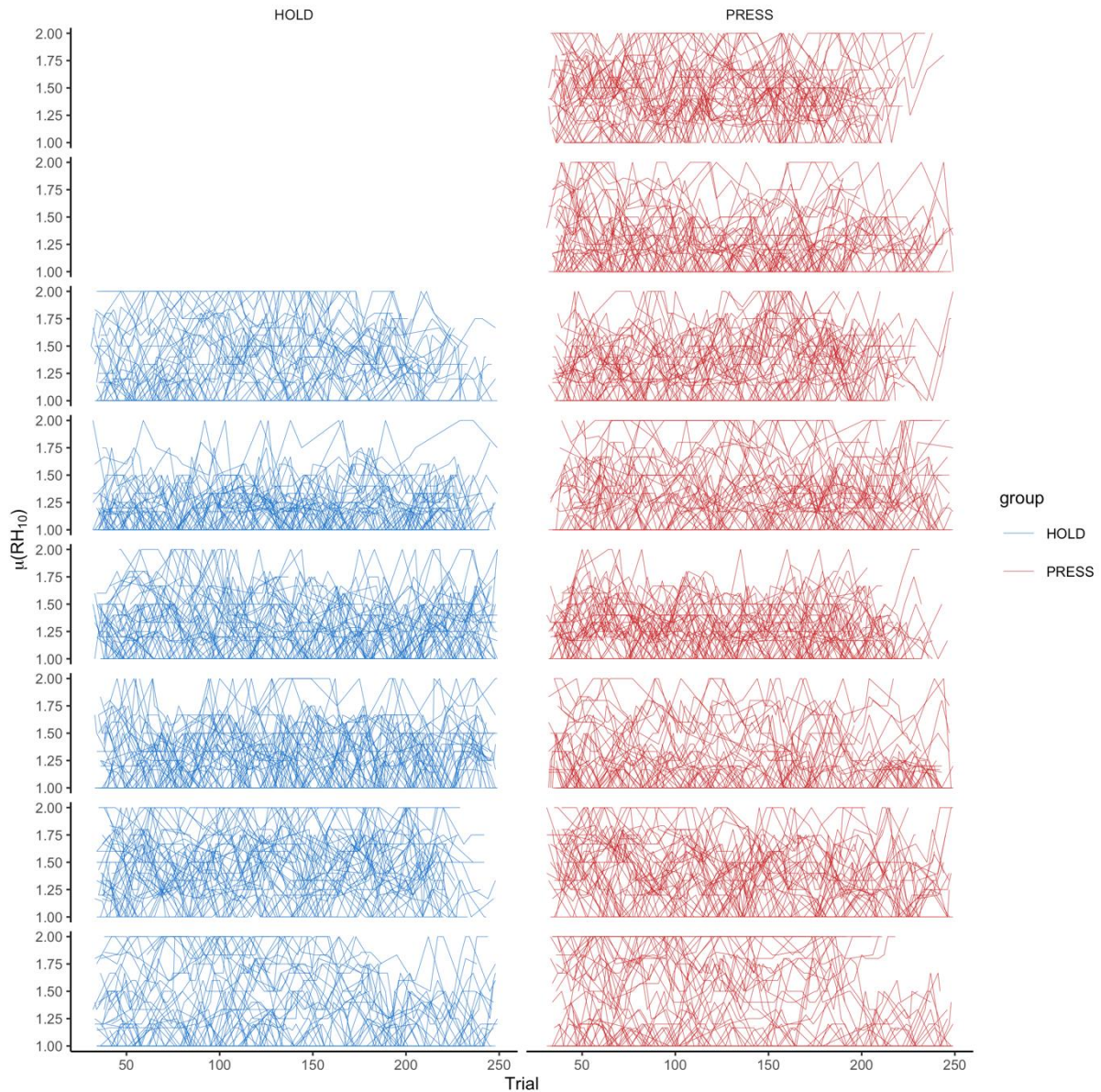
Model including previous TP



1
2 **Supplementary Figure 5B.** Results of GLMM fit including current TP and 15 previous trials as a
3 proxy for reward history. As opposed to Supp. Fig. 4A where amount of reward was used, here
4 TP were used. The formula in the plot shows specification of fixed terms in the GLMM. Asterisks
5 indicate significant terms. Error bars display confidence intervals of estimated effects.
6



7
8 **Supplementary Figure 6.** Results of GLMM fit including current TP and running average of last
9 10, 20, 30 TPs. TP history predictors were computed separately for rewarded (A) and
10 unrewarded trials (B). Significant model terms indicate that rats keep track of temporal errors
11 on current TP as well as TP history.
12

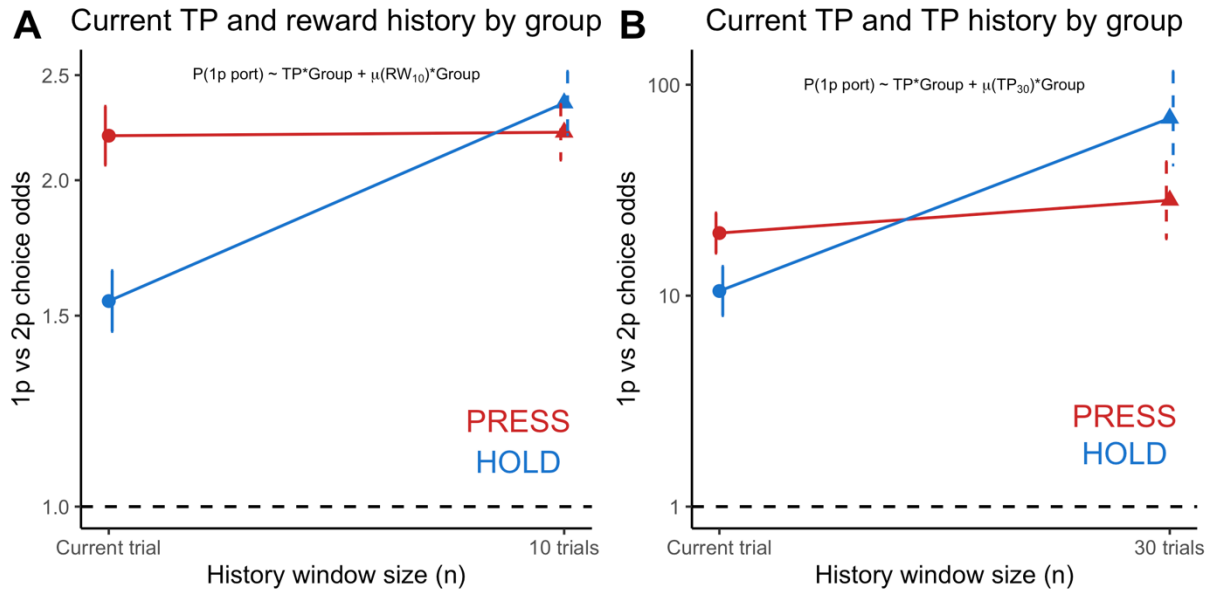


1
2 **Supplementary Figure 7.** Each panel depicts reward history (RH) traces for individual rats. Each
3 line originates from a single experimental session.

4
5 **S8. HOLD and PRESS groups keep track of temporal errors and reward history differently**

6 To understand what behavioral features are related to monitoring of temporal errors, we
7 hypothesized that HOLD and PRESS groups may differently utilize current temporal errors and
8 previous trial information such as reward history. We hypothesized that owing to its wider TP
9 distribution (Fig. 1B), the PRESS group could achieve better choice performance (Fig. 2). To test
10 whether PRESS and HOLD groups achieved their choice behavior differently, we re-fitted the
11 model including TP_n and the strongest factors reflecting previous trial information, that is μRH_{10}
12 and μTP_{30} (see Fig. 3BC). We added an interaction with group factor to each predictor (Supp
13 Fig. 7). As hypothesized, we found that HOLD and PRESS groups relied differently on current
14 trial TP (Fig S6A, $TP_n * \text{Group}: \beta = 0.33, SE = 0.046, z(16426) = 7.21, p < 10^{-12}$; Fig S6B, $TP_n * \text{Group}: \beta = 0.53, SE = 0.18, z(16965) = 2.97, p = 0.003$) and previous trial information (Fig S6A,
15 $\mu RW_{10} * \text{Group}: \beta = -0.09, SE = 0.047, z(16426) = -1.97, p = 0.049$; Fig S6B, $\mu TP_{30} * \text{Group}: \beta = -$
16 $1.08, SE = 0.34, z(16965) = -3.12, p = 0.002$). Notably the PRESS group tended to rely more on
17

1 the current TP, whereas the HOLD group relied more on previous trial information (TP and
 2 reward history), suggesting that the nature of motor sequence and associated variability
 3 contributed differently to choice behavior. Nevertheless, both PRESS and HOLD groups still
 4 relied on the current trial TP.
 5

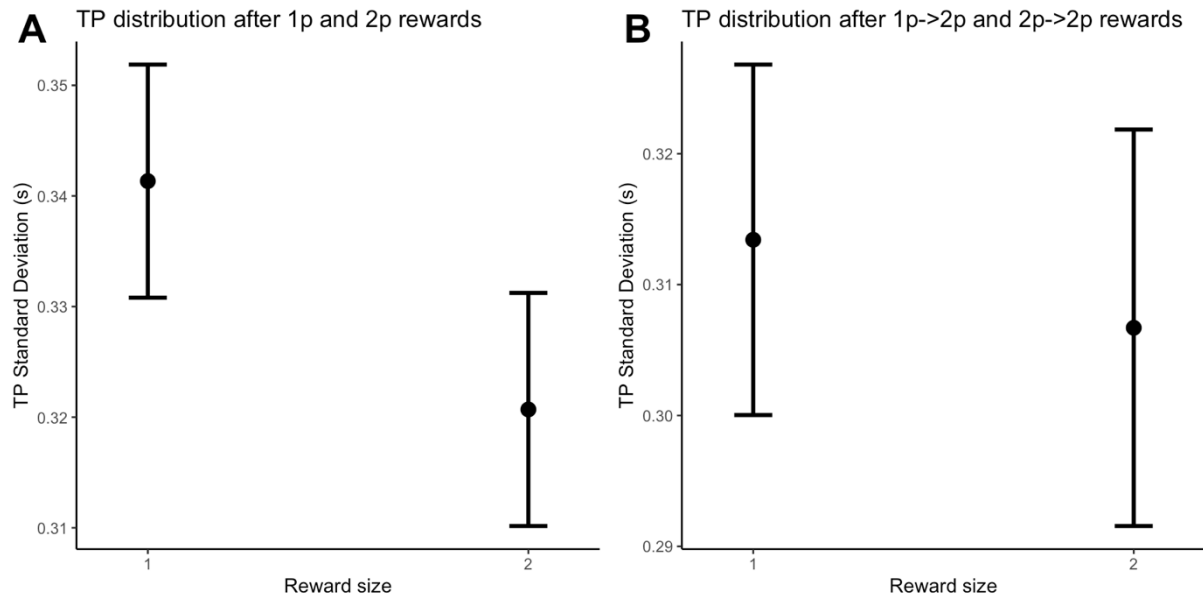


6
 7 **Supplementary Figure 8.** Results of GLMM fit including current TP and previous trial history. In
 8 conjunction with current TP, we tested μRW_{10} (A) and μTP_{30} (B).
 9

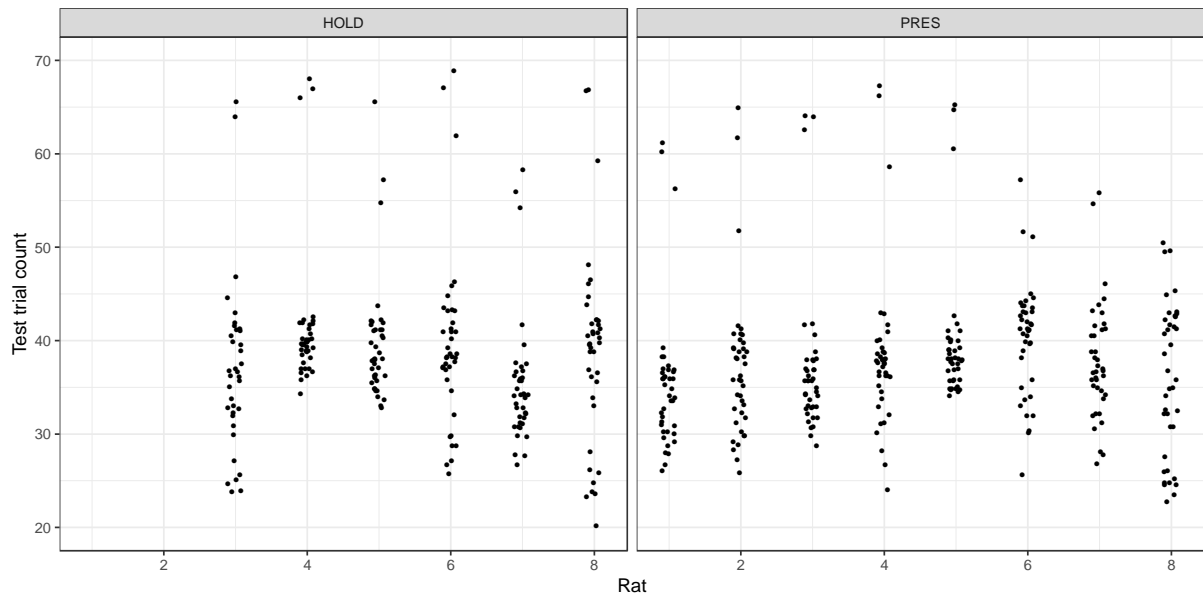
10
 11 **S9. Behavioral variability and hunting behavior (related to figure 4C)**

12 We considered a possibility that the hunting index could be affected by the degree of variability
 13 of a given rat, and that, as a result, it could affect the association between hunting and error
 14 monitoring. We addressed that concern in two ways. We verified that the addition of standard
 15 deviation of TP for each rat to the model including TP was not justified (Wald test: $W(1) = 0.03$,
 16 $p = 0.866$).

17 The other verification was based on the previous work in rat, monkey and humans
 18 indicating that reward magnitude calibrates performance variability on the next trial (Wang et
 19 al., 2019; Dhwale et al., 2019). We confirmed that TPs that followed TP_{SE-2p} had smaller
 20 variability than TPs that followed TP_{LE-1p} ($t(1009) = -4.13$, $p < 10^{-4}$; Supp. Fig. S9A). Given that we
 21 replicated the impact of variability in our data set, we compared TPs that followed a TP_{LE-1p} -
 22 TP_{SE-2p} sequence with those that followed a TP_{SE-2p} - TP_{SE-2p} sequence. TPs that followed these
 23 two types of sequences did not differ ($t(882) = -0.867$, $p = 0.39$; Supp. Fig. S9B). Together, these
 24 two analyses suggest that TP variance did not mediate the relationship between propensity of
 25 individual rats to monitor temporal error and to hunt for minimizing it.
 26

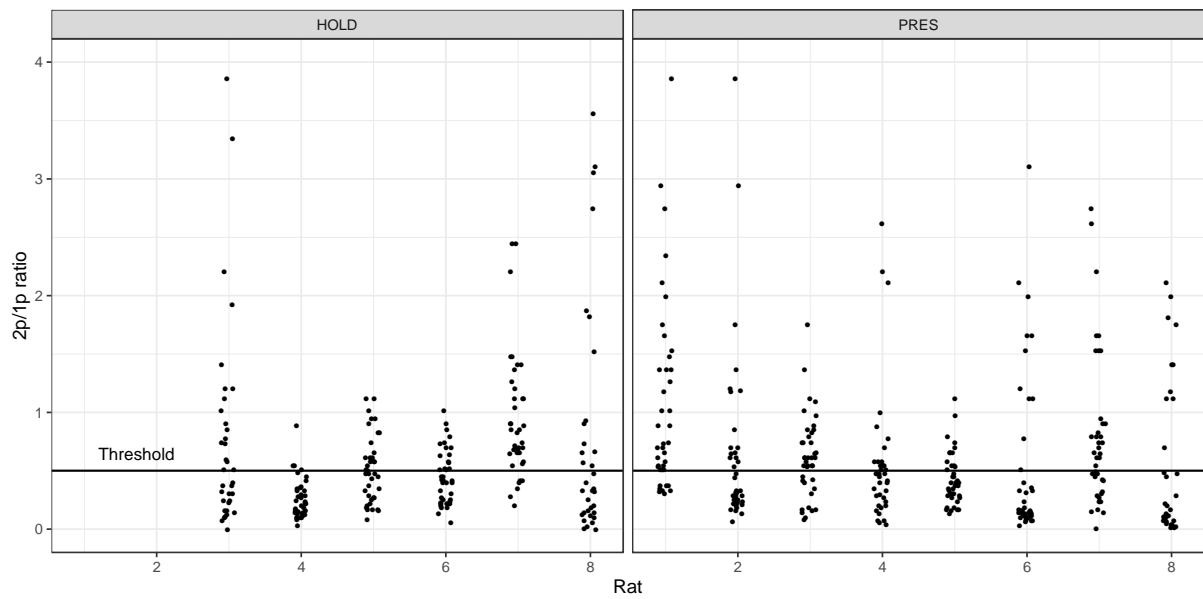


- 1
- 2 **Supplementary Figure 9.** Behavioral variability and hunting behavior (related to figure 4C).
- 3 (A) Standard deviation of TP preceded (n-1 trial) by 2p trials is smaller than those preceded by
- 4 1p trials.
- 5 (B) Standard deviation of TP preceded by '1p -> 2p' and '2p -> 2p' trial sequences (n-2 and n-
- 6 1) did not differ.
- 7



1
2 **Supplementary Figure 10.** The number of test-trials obtained per session per rat.

3
4



5
6 **Supplementary Figure 11.** 2p/1p ratios obtained per session per rat. The horizontal black line
7 displays Θ threshold.

8
9

10 **Supplementary Tables**

Group	Rat number	Wilcoxon test	p value	Session count > 55%
HOLD	1	96	4.4e-02	6
PRES	1	810.5	7.6e-08	35
HOLD	2	100	3.2e-03	3
PRES	2	519	1.9e-06	21
HOLD	3	595	3.8e-07	34
PRES	3	820	3.7e-08	35

Group	Rat number	Wilcoxon test	p value	Session count > 55%
HOLD	4	774	1.0e-06	24
PRES	4	805	1.1e-07	31
HOLD	5	754	3.9e-06	26
PRES	5	775	8.1e-08	33
HOLD	6	583	8.9e-05	23
PRES	6	727	2.7e-06	25
HOLD	7	811	7.3e-08	32
PRES	7	695	2.3e-07	31
HOLD	8	669.5	9.9e-05	24
PRES	8	455	1.9e-03	18

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Supplementary Table 1. Results of two-sided Wilcoxon test performed on test-trial accuracy for each rat separately. Test-trial accuracy on a single session served as a unit of observation for statistical testing. The last column displays the number of session where test-trial accuracy was above 55%.

TP Lag (n)	Beta estimate	z value	p value
0	16.94	34.4	3.0e-259
1	1.64	8.51	1.7e-17
2	1.43	6.25	4.0e-10
3	1.14	2.36	1.8e-02
4	1.22	3.47	5.1e-04
5	1.23	3.68	2.3e-04
6	1.25	3.8	1.4e-04
7	1.18	2.84	4.5e-03
8	1.3	4.59	4.5e-06
9	1.26	4.04	5.4e-05
10	1.1	1.65	9.8e-02
11	1.28	4.3	1.7e-05
12	1.24	3.88	1.0e-04
13	1.14	2.36	1.8e-02
14	1.3	4.61	4.0e-06
15	1.05	0.81	4.2e-01

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Supplementary Table 2. Detailed results of GLMM fit including current TP and rewards received on 15 previous trials. The values correspond to the data visualized in Supp. Fig. 4A.

TP Lag (n)	Beta estimate	z value	p value
0	17.69	34.27	2.4e-257
1	1.28	8.02	1.1e-15
2	1.24	6.96	3.5e-12
3	1.19	5.53	3.3e-08
4	1.29	8.35	6.6e-17
5	1.29	8.25	1.5e-16
6	1.39	10.88	1.5e-27
7	1.42	11.4	4.1e-30
8	1.44	11.81	3.4e-32
9	1.38	10.54	5.9e-26
10	1.36	9.91	3.7e-23
11	1.35	9.86	6.3e-23
12	1.32	9.06	1.4e-19
13	1.26	7.52	5.5e-14
14	1.31	8.87	7.5e-19
15	1.14	4.16	3.1e-05

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2 **Supplementary Table 3.** Detailed results of GLMM fit including current TP and 15 previous TPs
3 as a proxy for reward history and produced intervals. The values correspond to the data
4 visualized in Supp. Fig. 4B.