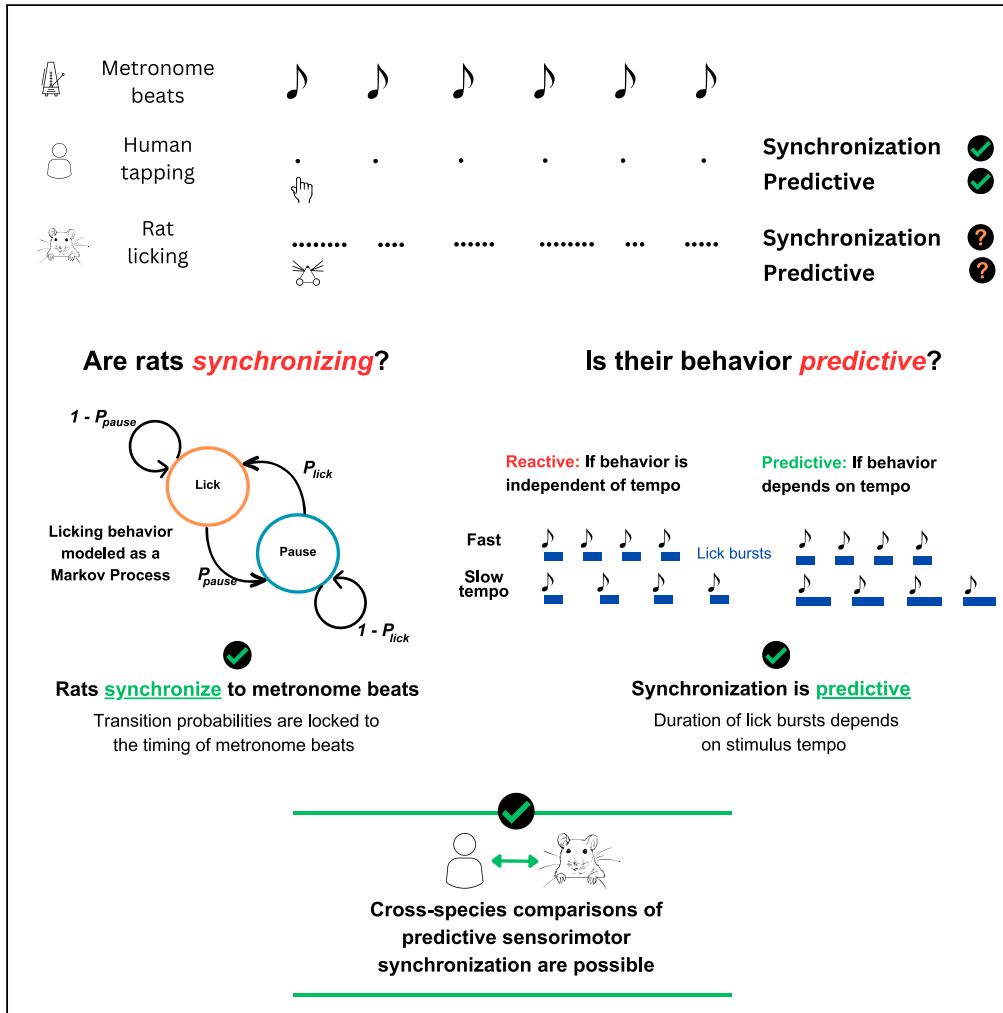


Article

Rats synchronize predictively to metronomes



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Highlights

A definition of sensorimotor synchronization that accommodates animal behavior

Different behavioral strategies expressed as simple Markovian models

Model comparison quantitatively distinguishes predictive from reactive behavior

Rats are capable of predictive synchronization to metronomes across a range of tempi



Article

Rats synchronize predictively to metronomes

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SUMMARY

Predictive auditory-motor synchronization, in which rhythmic movements anticipate rhythmic sounds, is at the core of the human capacity for music. Rodents show impressive capabilities in timing and motor tasks, but their ability to predictively coordinate sensation and action has not been demonstrated. Here, we reveal a clear capacity for predictive auditory-motor synchronization in rodent species using a modeling approach for the quantitative exploration of synchronization behaviors. We trained 8 rats to synchronize their licking to metronomes with tempi ranging from 0.5 to 2 Hz and observed periodic lick patterns locked to metronome beats. We developed a flexible Markovian modeling framework to formally test how well different candidate strategies could explain the observed lick patterns. The best models required predictive control of licking that could not be explained by reactive strategies, indicating that predictive auditory-motor synchronization may be more widely shared across mammalian species than previously appreciated.

INTRODUCTION

Studies of tapping behavior in humans have revealed immense insight into human beat perception and synchronization. A key feature of these studies is the demonstration that human auditory-motor synchronization is predictive. The observation that taps tend to spontaneously precede beats by tens of milliseconds¹ has set humans apart from other mammal species^{2–14} leaving mysterious the evolutionary and neurobiological origins of musical beat perception in humans. It has been hypothesized that beat perception and synchronization to complex sound patterns may have evolved as a byproduct of vocal learning,^{15,16} but several species that are not vocal learners nevertheless show some capacity for synchronization to external rhythms,^{7,8,11} suggesting instead that the required auditory-motor coordination may have developed gradually during mammalian evolution.¹⁷ Recent studies in macaques (a nonvocal learner) demonstrate the depth of insight gained through *in vivo* recordings during synchronization to simple periodic beat sequences (“metronomes”).^{18,19} However, the most commonly used laboratory mammals in neuroscience studies are rodents (rats and mice, also nonvocal learners). A clear demonstration of predictive synchronization in rodents would vastly expand the range of tools and approaches available toward understanding the neural mechanisms of beat perception and synchronization.

It is well-established that rodents are capable of precise timekeeping and temporal control of actions.^{20–25} Rodents are able to discriminate isochrony from non-isochrony,³ recognize familiar rhythms,²⁶ and show neural responses to auditory rhythms and music that support beat perception.^{27–29} Thus, rodents possess both an awareness of the global structure of sound sequences and a temporally precise control of action, two key elements of predictive synchronization. However, recent rat studies exploring synchronization to metronomes⁸ and to music,¹² while showing movements that were locked to beats, could not provide definitive evidence of anticipation.

We argue that requiring a human-like one-to-one beat-to-tap correspondence from animals who may have no ecological necessity to “tap to the beat” is highly limiting, since it overlooks the possibility that they may express predictive motor responses in other ways.³⁰ To cope with the varied forms that behavioral data from animals may take, we propose here a more general theoretical definition of predictive synchronization that allows a large degree of flexibility in how a predictive behavior might manifest itself. In particular, our definition allows for a one-to-many beat-to-action correspondence, provided that the timing of changes in the statistical properties of the actions are both *locked to*, and *vary with*, the beat rate. This definition eases the construction of models that can quantitatively make the tricky distinction between reactive and anticipatory behavior.

We developed a Markovian framework that models the one-beat-to-many-licks patterns produced by rats in a metronome synchronization task as an alternation between two behavioral states – licking and pausing—with transition probabilities that are modulated by external events (metronome beats and water rewards). Six models representing different strategies were developed, differing in the extent to which

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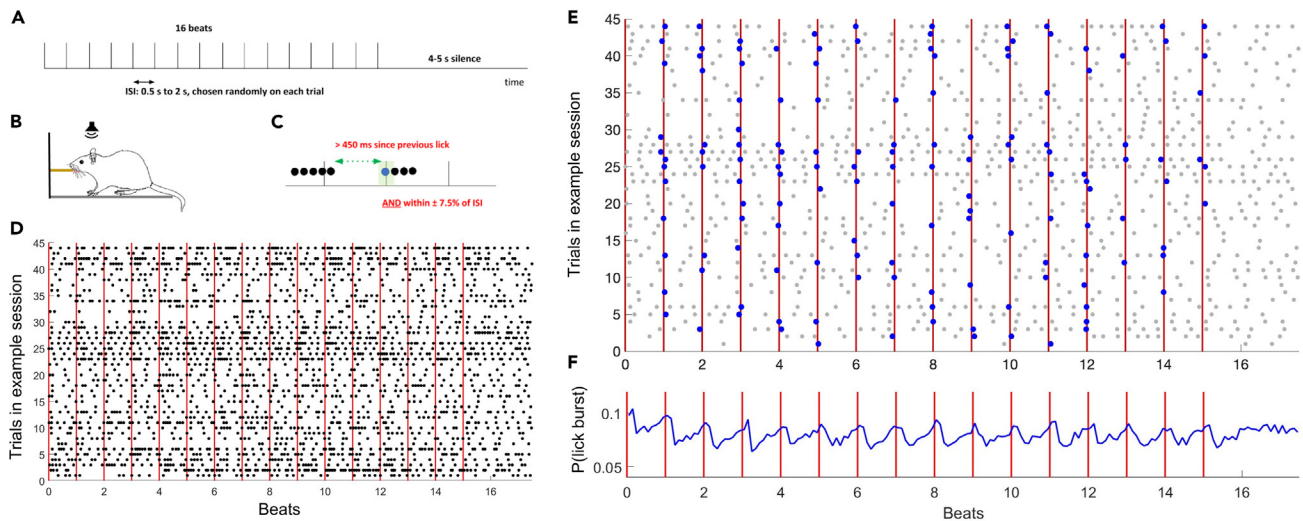


Figure 1. Task design and raw data

(A) Trials consisted of 16 isochronous metronome beats. The inter-stimulus interval (ISI) for each trial was selected randomly from a log-uniform distribution between 0.5 and 2 s. Trials were separated by 3–4 s of silence.
 (B) The rat was placed in a custom cage and sound was delivered by a speaker placed above the cage. The rat was trained to lick a water spout in synchrony with metronome beats.
 (C) The spout would immediately release a drop of water if a lick satisfied two conditions: that it was within $\pm 7.5\%$ ISI of a beat onset, and was separated from the previous lick by ≥ 450 ms.
 (D) Raster depicting licks in an example ~ 16 min session. Each row is one trial, and since every trial had its own tempo, time is normalized to the ISI of each trial.
 (E) Same data as (D), but showing only the first lick in each burst. Rewarded lick bursts are marked in blue.
 (F) A histogram of lick burst onsets around metronome beats, pooled across all sessions, trials, and animals. Y axis is the probability of lick burst onset in each $0.1 \times \text{ISI}$ bin.

the probability of licking depended on beat rate and timing. Models that included prediction—operationally defined as a modulation of transition probabilities that was locked to beats in a beat rate-dependent manner—consistently provided the best account for the data, demonstrating predictive auditory-motor synchronization in rats.

RESULTS

Rats lock their licking to metronome beats

The task (Figure 1) required rats to synchronize their licking with auditory metronomes across a range of tempi. Each trial consisted of 16 noise bursts with a constant inter-stimulus interval (ISI). An ISI was selected randomly for each trial from a log-uniform distribution between 500 ms and 2000 ms, and trials were separated by 3–4 s of silence. A small drop of water was delivered immediately (< 3 ms delay) if a lick satisfied two conditions: it was within a “rewarded time window” of $\pm 7.5\%$ ISI relative to sound onset, and it was separated from the preceding lick by at least 450 ms. This ensured that continuous licking was not rewarded, and to collect rewards at a high rate, the animals had to time their licks to coincide with the periodic noise bursts.

Data from a typical session are shown in Figure 1D. Licking in rats is governed largely by a central pattern generator in the brainstem³¹ that produces bursts with a rate of about 7 Hz (inter-lick intervals around 140 ms; for further discussion see STAR Methods). We defined a “lick burst” as a sequence of licks with inter-lick intervals shorter than 450 ms. Figure 1E shows only the onsets (the first lick) of each lick burst, with rewarded lick bursts highlighted in blue. While lick bursts were not produced exclusively at beat onsets, there was a clear modulation of lick burst probability around beats (Figure 1F). The results that follow use the onsets of lick bursts as the events of interest, since these triggered rewards when timed correctly.

Figure 2 illustrates the lick burst asynchronies, defined as the time difference between the onset of a lick burst and the nearest sound onset, produced by all animals across the range of tempi tested in this task. Since every trial had its own tempo, these asynchronies are expressed as relative times (centered around beat onsets, range -0.5 to $+0.5$ of the metronome period). The probability that the animals would initiate a lick burst was distributed non-uniformly around beats for all eight rats ($p < 10^{-5}$, circular Rayleigh test for uniformity, $N \approx 7,000$ – $11,000$ lick bursts per rat). As seen in Figure 2A, lick burst probabilities showed a distinct modulation pattern that was highly consistent across animals, increasing before the beat and decreasing following it. To test whether this pattern could have been observed by chance, a simple control simulation was performed that preserved the sequence of the observed lick bursts, but analyzed them as though they occurred during another randomly drawn metronome ISI (see STAR Methods). The shuffled lick burst asynchronies (Figure 2B) were not significantly modulated by phase for any of the rats ($p > 0.6$, Rayleigh test, $N \approx 6,000$ – $8,000$ shuffled lick bursts per rat). The mean asynchronies of lick bursts

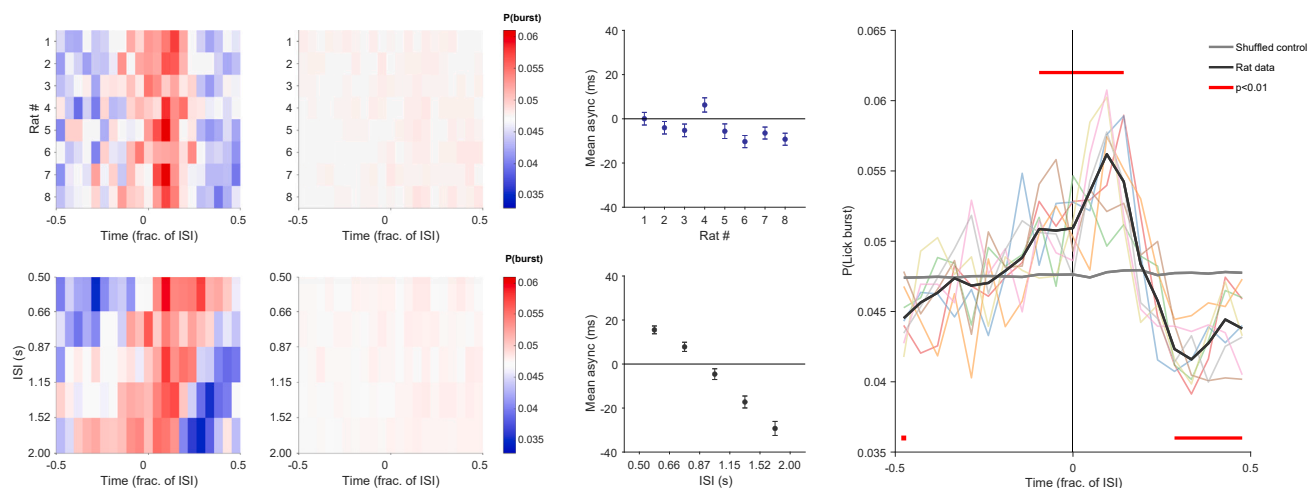


Figure 2. Rats significantly modulate their licking around metronome beats

(A) Probability of emitting a lick burst over the beat interval (normalized by ISI, -0.5 to $+0.5$), pooled across all trials of all rates ($N = 74,279$ lick bursts). Individual animals (rows) showed consistent licking patterns.

(B) Shuffled control for (A) (100 permutations).

(C) Mean asynchronies for individual rats \pm SEM; most are near zero or slightly negative.

(D) Probability of lick burst over the beat interval, pooled across animals and split into five tempo bins.

(E) Shuffled control for (D).

(F) Mean asynchronies by tempo bin \pm SEM. Asynchronies become more negative for longer ISIs (slower metronome rates).

(G) Grand average probability of lick burst, pooled across all animals and rates (black; See STAR Methods for details of this calculation). Individual animals are shown by the colored lines (same data as in A), and the grand average shuffled control is shown in gray. Time bins where lick burst probability is significantly different from the shuffled control are marked in red ($p < 0.01$, permutation test with False Discovery Rate correction using Benjamini-Hochberg step-up procedure, 100 permutations).

were on average close to zero or negative for most rats, indicating a mean tendency for lick bursts to start just before the impending noise (Figure 2C).

To explore how lick burst asynchronies varied with tempo, trials were split into five log-spaced tempo bins and pooled across all animals (Figure 2D). Lick burst probability was significantly modulated by phase in all tempo bins ($p < 10^{-6}$, Rayleigh test, a total of $N \approx 8,000$ – $24,000$ lick bursts per tempo bin). The same analysis performed on the shuffled data showed no modulation in any tempo bin (Figure 2E; $p > 0.3$). The mean asynchronies (Figure 2F) reflect the monotonic shift toward more negative values with increasing ISIs that is apparent in Figure 2D (see Figures S1 and S2 for finer-grained analyses of lick burst asynchronies by ISI and by animal), hinting at predictive control of motor timing that has also been reported in other species.^{11,32} The grand average histogram of the lick rates, pooled across all animals and tempi, shows an overall modulation of approximately 30% of the baseline probability (Figure 2G). The data show significant deviations from the shuffled control at many phases, including some before the beat. After the end of the 16 beat sequence, rats also produce a similar lick burst profile in the anticipation of the 17th (silent) beat (see Figure S3). However, the data also hint at reactive elements, for example in the fact that the peak in lick burst probability occurs after the beat. Such a combination of features makes it difficult to conclude that the rats are anticipating upcoming beats, motivating the need for a quantitative modeling approach that can address this question.

Are rats reacting or predicting? A test of six possible strategies

To determine whether the observed patterning of lick bursts around beats reflects predictive synchronization, we developed a Markovian framework by which different underlying behavioral strategies can be modeled and compared. The state graph of the Markov process is shown in Figure 3A and is shared by all models. The graph has two branches, a **Lick** branch that consists of states traversed while the animal is in a lick burst, and a **Pause** branch that consists of states traversed while the animal is not licking. The states along a branch represent the time elapsed while the animal is licking or pausing. The crucial assumption in all models is that the transition from one process state to the next one depends only on the current process state (although it may vary in time). Given this Markovian assumption and the fact that the model states are fully observed (no latent states need to be estimated), the overall probability of an observed trial is simply given by the product of the probabilities of the transitions that occurred at each time step during the trial (Figure 3A).

This modeling framework is powerful in that it is not limited to the one-to-one beat to action relationship typical of human synchronization behavior, and the transition probabilities can be made sensitive to the timing of external events, such as metronome beats (see STAR Methods). Importantly, the modulation of transition probabilities by metronome beats reflects predictive synchronization if this modulation depends on the tempo (see STAR Methods for a conceptual explanation of how the same framework applies to the simpler

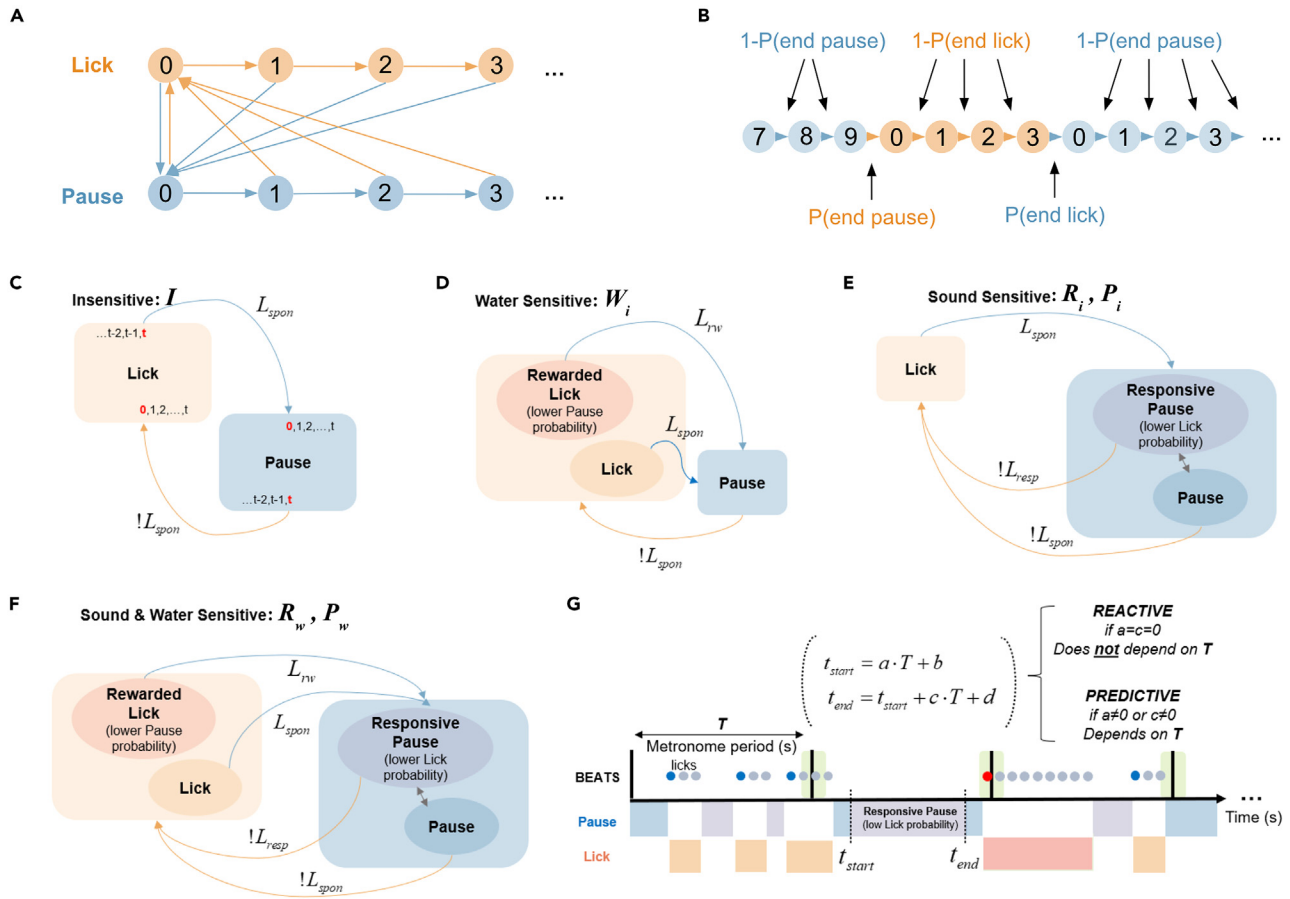


Figure 3. Modeling approach, with candidate strategies represented as Markov processes

(A) A graph of the Markov process. The two branches correspond to lick bursts (orange) and pauses (blue), each modeled as a succession of process states, one for each time bin of the data (10 ms bins used here). Transitions are either forward along the branch or back to the state corresponding to time 0 of the other branch. Thus, the termination of a lick burst is followed by a sequence of Pause states, and the termination of a pause is followed by a sequence of Lick states. (B) A schematic illustrating a trial decoded into the process states of the Markov process shown in (A). A Pause lasting 10 time steps is followed by a Lick lasting 4 time steps, followed by another Pause. All transition probabilities depend only on the current process state. The overall probability of this segment is the product of these transition probabilities.

(C) The **Insensitive** model assumes an alternation between the Lick and Pause states with no dependence on external events. The transition probabilities are time-invariant.

(D) In the **Water Sensitive** model, the transition probabilities of the Lick state depend on whether the lick burst is rewarded, as determined from the actual time course of the trial.

(E) In the **Sound Sensitive** model, transition probabilities of the Pause state depend on the time since the last metronome beat. The tempo-dependence of the start and end of these “responsive windows” determine whether the model is Reactive or Predictive.

(F) The **Sound and Water Sensitive** model combines the features of the Sound Sensitive (Responsive Pauses) and Water Sensitive (Rewarded Licks) models.

(G) Schematic representation of the traversal through states in the time-dependent models of (F). A hypothetical lick pattern is shown with licks in gray and the lick burst onset in blue if unrewarded, and in red if rewarded. Below the black lines representing the metronome are how the Sound and Water Sensitive models would parse the state that the animal is in, with the two types of Pause states in blue (spontaneous) and purple (responsive), and the two types of Burst states in orange (unrewarded) and red (rewarded). The boundaries of the Responsive Pause are determined (as in Equation 1 of the main text) by four parameters: a , b , c , and d . The model is Reactive if a and c are both set to 0, or Predictive if a or c are nonzero.

case of one-to-one tapping). We used this approach to construct models representing a range of candidate strategies for producing the observed data, with the specific aim of quantitatively assessing whether the rats were indeed synchronizing their lick bursts predictively to the metronomes.

The simplest possible strategy available to the rat is to ignore the metronome and initiate lick bursts at random. We modeled this strategy by assuming that the animal switches between the Lick and Pause states with constant transition probabilities that are independent of sound stimuli or water rewards (a simple Markov chain with the state graph of Figure 3A). In Figure 3C, as well as later Figures and Tables, we denote the transition (exit) probability from the Lick state as L_{spont} , the transition probability from the Pause state as $!L_{spont}$. Since, for this

simple strategy, transition probabilities do not depend on external events, we call this the **Insensitive** model (Figure 3C), abbreviated henceforth as *I*.

Next, the **Water Sensitive** model (Figure 3D) was designed to accommodate the observation that rewarded lick bursts had longer durations than unrewarded lick bursts. In the Markov framework, this can be expressed by postulating two sets of transition probabilities for a lick burst, one for rewarded licks (denoted L_{rw} in Figure 2D) and another for unrewarded licks (denoted L_{spont}). Note that the rewarded and unrewarded lick bursts are not two different states – rather, both are the same Lick state, but with different transition probabilities. The nature of the lick burst (rewarded or unrewarded) is not probabilistic – it is fully determined by its timing relative to a metronome beat. Once a lick burst starts, it remains of the same type throughout. Also note that this model does not assume any sensitivity to the metronome beat, and in fact, is reduced to the insensitive model when the transition probabilities for the rewarded and unrewarded lick bursts are identical. The insensitive model is therefore “embedded” within the water-sensitive model, and we abbreviate this model as **W_i** to reflect the embedding. Model embedding is a key feature in the construction of all models, making it possible to directly compare their likelihoods of producing the observed data.

The next class of models consists of two **Sound Sensitive** models. These models incorporate a sensitivity to the metronome that may be either **Reactive** or **Predictive**, as explained later. The main experimental observation (Figure 2G) is a higher rate of lick bursts around metronome beats and a lower rate between them. We conceptualized this as a strategy in which the rat deliberately suppresses its licking during a time interval that starts shortly after a metronome beat and ends before the next one (Figure 3E). We consider this period of lower lick burst rate as the *response* of the rat to the metronome beat, and therefore call the pauses during that time “responsive pauses,” as opposed to spontaneous pauses that occur outside of this window. Again, spontaneous and responsive pauses are not different states, but rather the same Pause state with different transition probabilities. Thus, a Pause can start as spontaneous, extend into the responsive period, and even extend back into the spontaneous period (the double arrow in Figure 3E). A pause therefore follows the sequence of process states of the Pause branch, but the transition probabilities change for the process states that occur while the pause is in the responsive window, and change again if the pause extends beyond the responsive window. The sound-sensitive models also reduce to the insensitive model if the transition probabilities of the responsive pause and spontaneous pause are equal; thus, we abbreviate these models as **R_i** and **P_i**.

The last class of models, the **Water and Sound Sensitive** models (Figure 3F), incorporate water sensitivity into the sound-sensitive models. Transition probabilities of the Lick state depend on water rewards and transition probabilities for the Pause state depend on metronome beats. If the transition probabilities of spontaneous and responsive pauses are equal, these models reduce to the Water sensitive model **W_i**. Thus, we abbreviate the reactive and predictive versions of these models as **R_w** and **P_w**, respectively.

In the sound sensitive models (**R_i**, **P_i**, **R_w**, **P_w**), a responsive window occurs between every two metronome beats, at the same intervals relative to the most recent metronome beat. We denote the times at which the transition probabilities of the Pause state shift from spontaneous to responsive and back (relative to the previous metronome beat) by t_{start} and t_{end} . The dependence of these intervals on the period of the metronome is our main argument for the presence of predictive synchronization. We parametrized the start and end of the responsive window (with time $t_{start} = aT + b$ being the most recent metronome beat) by:

$$t_{end} = t_{start} + cT + d \quad (\text{Equation 1})$$

where T is the metronome beat period (in seconds), the parameters a and c are unitless fractions of the beat interval (bounded between 0 and 1), and the parameters b and d are in seconds (constrained to be between -0.5 and 0.5 s (b) or -1 and 1 s (d); the optimized values are inside this range). In Reactive models, the parameters a and c were constrained to be zero, so that the responsive window begins b seconds after each beat and ends $b+d$ seconds after the beat, regardless of tempo. Such responsive windows can be viewed as triggered by the previous metronome beat, and do not require any prediction of the next beat. When a and/or c are nonzero, the timing of the responsive window becomes dependent on the beat period. Such responsive windows can still be viewed as triggered by the previous metronome beat, but require the existence of an internal representation of the beat period T . Therefore, such models reflect a predictive strategy.

We parametrized the transition probabilities of Figure 3A by a small number of parameters, allowing the different strategies illustrated in Figure 3 to be quantitatively compared (see STAR Methods for details). Each model was optimized by finding the parameters that maximized that model’s likelihood to produce the observed data. The optimized likelihoods of embedded models were then compared using χ^2 tests, allowing us to test the null hypothesis that $a=c=0$.

Rats predictively time their licking

Table 1 and Figure 4A compare the log-likelihoods of the different models, using the Insensitive model as a reference. Water sensitivity substantially improved model fits, compared to the corresponding models without water sensitivity (first three rows of Table 1). Sound sensitivity also substantially improved the fit to the data (rows 4–5 of Table 1). Our critical finding is that the best fits the data were produced by the predictive models where responsive pause windows were tempo-dependent (rows 6–7 of Table 1). The water-sensitive Predictive model (**P_w**) was the winning model, outperforming the second best model, the water-sensitive Reactive model (**R_w**), by a highly significant 95 log likelihood units ($\chi^2(2) = 190$, $p < 10^{-41}$).

We used the optimized parameter values to compute the lick burst probabilities around beats for each model (Figure 4B). As expected, the Insensitive model with its fixed, time-invariant transition probabilities, produces no structure at all in the timing of lick bursts. The estimated burst rate of the Insensitive model, and indeed all models, is identical to the average burst rate of the data ($\mu = 0.048$ per 0.1^*1 SI bin, Figures 4B

Table 1. Summary of model comparisons

	Comparison	Δ LL	Δ df	p-value
1	$W_i - I$	8819	1	0
2	$R_w - R_i$	8819	1	0
3	$P_w - P_i$	8819	1	0
4	$R_i - I$	319	3	10^{-137}
5	$R_w - W_i$	319	3	10^{-137}
6	$P_i - R_i$	95	2	10^{-41}
7	$P_w - R_w$	95	2	10^{-41}

I: Insensitive model, W_i : Water sensitive model, R_i : Reactive model, P_i : Predictive model, R_w : Reactive model with water sensitivity, P_w : Predictive model with water sensitivity. The near-identical differences in log likelihoods (rows 1–3; rows 4–5; rows 6–7) result from the fact that each level of complexity (water sensitivity, sound sensitivity, and tempo-dependence, respectively) affects a different set of parameters and different sets of states. Thus, W_i and I , R_w and R_i , and P_w and P_i differ only in the addition of water sensitivity, which increases the likelihood of long lick states; R_i and I as well as R_w and W_i differ in that sound sensitivity affects the duration of the pauses through the b and d parameters of Equation 1; and P_i and R_i , as well as P_w and R_w , differ in the tempo-dependence through the a and c parameters.

and 4C). All other models, including the W_i model that has no direct dependence on the stimulus, showed the modulation of the rates of lick bursts around beat times. However, the introduction of sound sensitivity through responsive pauses with predictive timing substantially improved the fit to the data. The superior fit of the predictive P_w model compared to the reactive R_w model is illustrated in Figure 4D. The predictive model captures very well the time at which the lick burst rate increases before the beat (green line), while the reactive model (orange line) shows no increase in the lick burst rate. This happened because the optimized duration of the responsive window for the R_w model was 0.8 s (see Tables S1 and S2 for parameter logic and optimized values for all models), which covered the whole interval between beats for shorter metronome periods. Thus, the reactive model, with its fixed responsive pause window, is unable to account for the period-dependent changes in lick burst rate present in the data (see also Figure S4).

The optimized parameters provide further information on the strategies used by the rats to solve the task (see STAR Methods for a detailed description of parameters and Tables S2). Rewarded lick bursts were indeed longer (had a smaller exit probability) than unrewarded ones. Similarly, transition probabilities out of responsive pauses were lower than out of spontaneous pauses, as hypothesized. Figure 4E visually compares the optimized Responsive Pause periods for the two best models (P_w , R_w), determined by the a , b , c , and d parameters in Equation 1. The beginning of the Responsive Pause (the transition from red to blue at positive phases) is identical in the two models, at 300 ms after each beat, strongly suggesting that the rats indeed begin suppressing their licking in reaction to the beat. However, the end of the Responsive Pause (the transition from blue to red) differs between the two models. It occurs later at slower tempi in the predictive model, reflecting

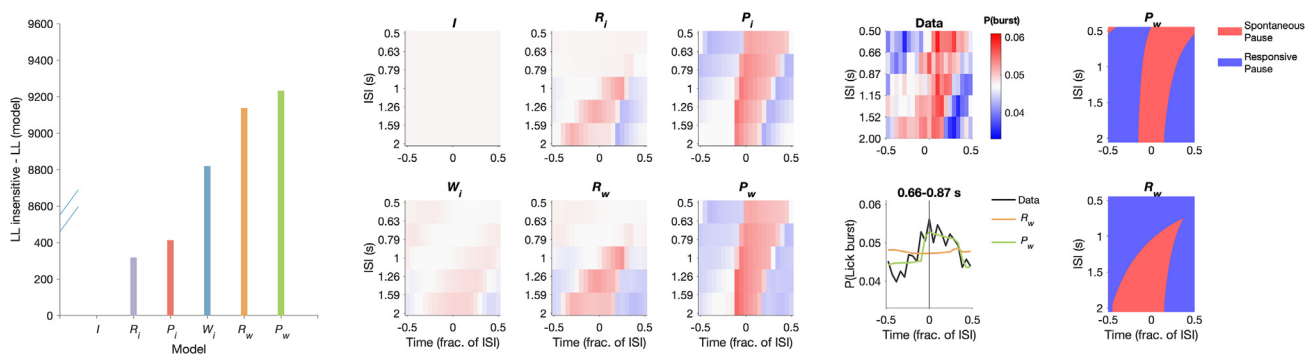


Figure 4. Lick patterns are best explained by a predictive model

- (A) Log-likelihoods of the candidate models, referenced to the Insensitive model. Note the break in the y axis underneath the water sensitive models.
- (B) Each panel depicts probability of lick bursts split by tempo bin based on the six models tested (I : insensitive, R_i : reactive, P_i : predictive, W_i : water sensitive, R_w : reactive + water sensitive, P_w : predictive + water sensitive). Note that the Insensitive model in particular shows no modulation at all and that the probability of a lick burst is constant and equal to the mean.
- (C) Observed licking rates in five tempo bins (same as Figure 2D, reproduced here to ease comparisons).
- (D) Data versus the R_w (orange) and P_w (green) models for an intermediate tempo bin. Note that the predictive model better captures the timing of the rise and fall in lick burst probability compared to the reactive model. See also Figure S2.
- (E) The temporal extent of the Responsive Pause period (blue) across tempi, based on the optimized a , b , c , and d parameters. The spontaneous pause, characterized by a higher probability of emitting a lick burst, is shown in red. The winning predictive P_w model (top) allows for lengthening of the responsive pauses with faster tempi relative to the R_w model (bottom), improving the fit to the data.

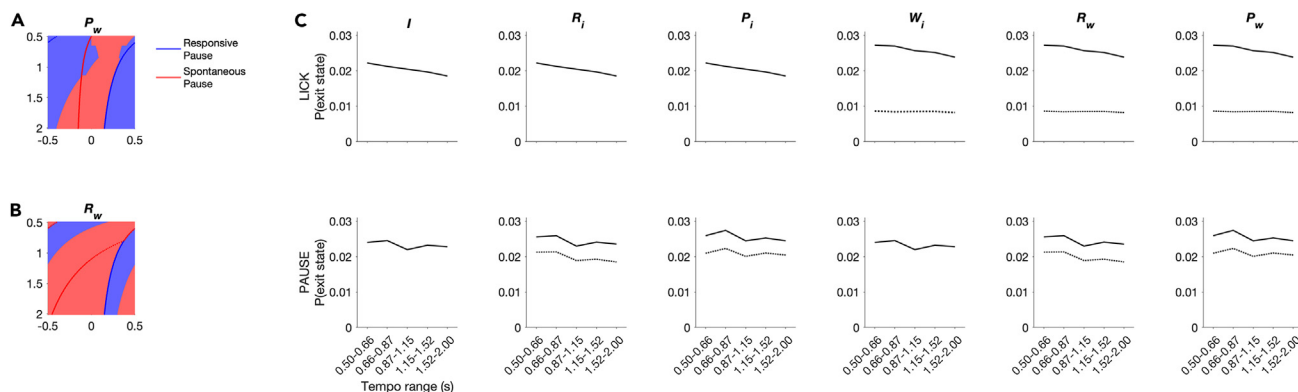


Figure 5. Optimized parameter values reveal further sensitivity to tempo

(A) Optimized temporal boundaries of Responsive Pause periods for the 5-group P_w model. The lines depict the temporal boundaries of the 1-group model for comparison.

(B) Same as A, but for the R_w model. See also Figure S5.

(C) Optimized probabilities of exiting the Lick (top row) or Pause (bottom row) state for each of the six models (columns). For the Lick probabilities (top row), dashed lines represent the exit probabilities during the rewarded licks. For the Pause probabilities (bottom row), dashed lines represent the exit probabilities during the responsive pauses.

a longer suppression of licks (blue) at slower tempi compared to the reactive model. Thus, rats are timing their exit from this suppressed state of licking based on an internal prediction of when the next beat will occur.

Rats shorten their lick bursts at faster tempo

Our findings raise two related questions. First, is the dependence of the responsive pause window on tempo indeed linear, as our predictive models so far assumed, or are there non-linearities in this dependence? And second, are there any other model parameters that are tempo-dependent?

To address these questions, we ordered trials by tempo and split them into five groups, with approximately equal numbers of trials in each tempo group. All six models were fitted onto the trials in each tempo group. For the Sound Sensitive models, we added the additional constraint that the a , b , c , and d values should result in t_{start} and t_{end} values that were within a 100 ms tolerance at the boundaries of neighboring tempo groups, based on the intuition that the animal should not change its strategy abruptly from one tempo to the next. We refer to these as the 5-group models, and the models described previously as the 1-group models.

The results of the 5-group analysis re-confirm that the predictive P_{w5} model is the best-fitting model overall and outperforms the next best-fitting reactive R_{w5} model by a substantial margin ($\chi^2(10) = 220$, $p < 10^{-41}$). This difference is only slightly larger if the continuity constraint between neighboring tempo bins is removed ($\chi^2(10) = 295$, $p < 10^{-57}$; see Figure S5). Despite the R_{w5} model no longer being truly “reactive” (its parameters vary between tempo groups), the P_{w5} model still outperforms the R_{w5} model by at least 18.5 LL units in each tempo group individually ($\chi^2(10) > 37$ in each tempo group, $p < 10^{-4}$; see Table S3).

Figure 5 shows the optimized parameter values derived from the 5-group models. Fitting models to data split by tempo improved the model fits substantially for all models, indicating that indeed other aspects of rat behavior were modulated by tempo (I : $\chi^2(12) = 619$, $p < 10^{-50}$; W_i : $\chi^2(16) = 446$, $p < 10^{-50}$; R_i : $\chi^2(16) = 701$, $p < 10^{-50}$; P_i : $\chi^2(24) = 628$, $p < 10^{-50}$; R_w : $\chi^2(20) = 527$, $p < 10^{-50}$; P_w : $\chi^2(28) = 455$, $p < 10^{-50}$). In spite of the 5-group model having greater freedom in setting the temporal boundaries of the Responsive Pause, the 5-group models determined relatively similar Responsive Pause periods to the 1-group models as a function of tempo (Figures 5A and 5B), suggesting that the linear assumption of the 1-group model is appropriate given the data (see Figures S6 and S7 for responsive periods and data expressed as a function of absolute time rather than relative time).

Thus, the improvements in fit for the 5-group models must have been primarily due to the rats adjusting their transition probabilities by tempo. Figure 5C shows the tempo-dependence of all the transition probability parameters for the 5-group models (probability of exiting the Lick state: top row; Pause state: bottom row), with dashed lines representing the “responsive” version of the respective behavioral state (top: Rewarded Lick; bottom: Responsive Pause). Most of the transition probabilities did not depend strongly on tempo, including the transition probabilities out of the responsive Pause (Figure 5C bottom, dashed lines), spontaneous Pause (Figure 5C bottom, solid lines), and rewarded Lick (Figure 5C top, dashed lines). However, the probability of exiting the unrewarded Lick state (Figure 5C top, solid lines) showed a clear tempo-dependence, decreasing monotonically with longer beat periods. This tempo-dependence was present in all 5-group models, showing that this parameter accounted robustly for properties of the unrewarded licks. We interpret this as reflecting a behavioral strategy where the rats shortened their unrewarded lick bursts at faster tempi (see Figure S8). This strategy would make it easier for the rats to observe the minimum break duration required to get the reward. Such a

strategy by itself may improve success rate, but is not strictly predictive, since it does not entail locking to metronome beats. Together, these results reveal that the rats synchronized their licking to the metronomes using a mixture of predictive and non-predictive strategies.

DISCUSSION

This study presents an exploration of behaviors that previously may have been dismissed as intractable for studying auditory-motor synchronization. Two conceptual advances are presented here. First, we provide a flexible, task-agnostic modeling approach that enables rigorous comparison of candidate behavioral strategies in producing an observed behavior. Second, we provide the most concrete evidence to date that rats are capable of predictive synchronization in a range of tempi compatible with human behavior. These advances are based on a more general theoretical definition of predictive synchronization, which resolves the hurdle posed by the fact that the rats showed a one-to-many beat-to-action synchronization behavior. Using this definition allowed us to explicitly demonstrate that rats adopted a predictive strategy in synchronizing their licking to metronomes.

Our study shares similarities with previous studies of auditory-motor synchronization in rats but also complements them in crucial ways. One previous metronome synchronization study in rats⁸ employed lever-pressing and revealed that rats produced a behavior that was clearly tempo-matched to the stimulus. However, that study did not provide evidence that the synchronization was predictive. Here, we discovered that rats terminated a period of suppressed licking between beats as a function of the metronome period, thus showing an anticipation of the next beat. It is worth noting that the reward window differed greatly between the two tasks. Katsu and colleagues employed a reward window that included a large fraction (>70%) of the inter-stimulus interval, with most of the reward window occurring *after* the beat. With such a reward window, rats would not gain much by adopting a predictive strategy. In our task, the window for reward was short ($\pm 7.5\%$ of the inter-stimulus interval) and symmetric around beat onsets, so that anticipation was presumably highly advantageous for optimizing reward, given that the baseline success rates for random licking would have been very low, and use of purely reactive strategies would have required implausibly fast reaction times. These differences in task design may also be responsible for the positive mean asynchronies observed by Katsu and colleagues, in contrast to the negative mean asynchronies observed here (see [Figure 2F](#)).

A study that explored spontaneous synchronization to beat in rats listening passively to music¹² found head movements that were locked to beats. However, that study did not demonstrate that these head movements included a predictive component. Curiously, these synchronized head movements were only present during the first experimental session, which is suggestive of startle-like reactions that habituate rapidly. Similar spontaneous and seemingly involuntary facial movements locked to a rhythmic auditory sequence have recently been reported in head-fixed mice as well and were extinguished when associated with an aversive stimulus.³³ To the extent that these involuntary responses share neural circuitry with the networks responsible for voluntary auditory-motor synchronization, startle responses may prove to be an important component of the synchronization process. Our modeling approach may in fact help quantify the subtle ways in which unreinforced or involuntary behaviors in the absence of a task may still be driven by an external stimulus. For example, our framework could be applied to test whether such involuntary movements are executed predictively when the auditory rhythm is predictable – reflecting a spontaneous form of predictive synchronization – or whether they follow the salient stimulus events with a short but fixed latency. Such models can therefore link task-free studies of unreinforced auditory-motor synchronization¹² with studies of reinforced behaviors such as ours.

To our knowledge, the use of Markov processes with transition probabilities that are responsive to external events for modeling sensorimotor synchronization is novel. It differs from existing models of sensorimotor synchronization, which have typically taken dynamical systems approaches,^{34,35} Bayesian approaches,³⁶ or a combination of the two.³⁷ Here, we engage directly with the observed behavior without making a commitment to mechanisms (as dynamical systems models do) or to normative accounts (as Bayesian models do). Our approach is more similar to “event-based models” that intend to predict the next event based on previous events, although such models do hypothesize underlying mechanisms^{38–40} while our approach does not. Importantly, our modeling approach breaks conceptual ground by shifting from a view of the one-to-one beat-to-tap correspondence as reference for all aspects of sensorimotor synchronization, which is an idealization even when considering only humans, to one that is based on unbiased modeling of the observed behavior. Our models and their parameters are directly interpretable in terms of observed behavior, enabling the identification of both predictive and non-predictive strategies that contribute jointly to synchronization.

One important limitation of this study is that only isochronous stimuli were employed, while in the human literature, perturbations are additionally used to demonstrate predictive behavior.^{41,42} While the use of isochronous stimuli facilitated the development of a simple Markovian framework to explore this challenging behavioral dataset, it is obviously of great interest to test whether rat performance in the presence of predictable tempo changes or unpredictable perturbations is similar to that of humans. The present work could easily be extended in this direction, for example by experimentally employing tempo-variable stimuli and adding an additional “external” cue to the model – a Δ ISI – that captures the difference between successive intervals between beats. This extended framework would contain within it the isochronous case, while flexibly accommodating the exploration of perturbations and tempo changes. Such a follow-up study would potentially strengthen the causal relationship between stimulus timing and behavioral response, and establish a stronger connection with human work on sensorimotor synchronization.

Since our approach enables the extraction of general strategies that may be employed by any species, human or nonhuman, we believe this approach can lead to a more nuanced insight into human sensorimotor synchronization as well. Proficient auditory-motor synchronization is often taken for granted in humans, despite high variability between individuals^{41,42} and the existence of high and low synchronizers.^{43,44} We

conjecture that humans too employ a mix of predictive and non-predictive strategies while synchronizing, with this mix depending on the individual, the stimulus, the effector producing the action, as well as motivational and informational factors.

Given our framework's generality in quantifying the probability of events linked to external stimuli, this approach could even be applied to neural activity. Modeling a neuron's probability of spiking throughout a beat interval, for example, could help in differentiating responses evoked by, versus those entrained to, rhythmic sensory input.^{45–48}

Finally, our findings have implications for theories of the evolutionary origins of rhythm perception and auditory-motor synchronization. They challenge the vocal learning hypothesis⁴⁹ by demonstrating that the rat, a nonvocal learner, can be trained to synchronize predictively to metronomes across a wide range of rates. Indeed, based on our findings and combined with existing evidence that the processing of sound by the mammalian auditory system influences subjective beat perception, we believe that rats may be capable of true beat perception through synchronization to a subjective beat in music or other complex stimuli. The gradual audiomotor evolution hypothesis suggests that the capacity for rhythmic entrainment developed gradually across primates, peaking in humans but present to a limited degree in non-human primates.¹⁷ Our results support this hypothesis, and further extend it to cover a wider range of mammalian species. In consequence, our findings build a potential bridge between the extensive electrophysiological work done in rodent models on timekeeping during relatively simple tasks^{20–25} with the growing insight coming from *in vivo* recordings of nonhuman primates synchronizing to metronomes.^{18,19,50,51} Beyond its biological and evolutionary implications, this work demonstrates the feasibility of the study of beat perception and synchronization in rodent models and facilitates direct comparisons of the dynamics of sensorimotor entrainment as they vary across species in the animal kingdom.

Limitations of the study

As mentioned in the discussion, one limitation of this study is that only isochronous stimuli were used, whereas human literature details sensorimotor synchronization responses to stimuli with perturbations such as omissions, delays, and changing tempi. Follow-up studies may potentially explore these dimensions using the modeling approaches developed here.

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by the lead contact, Dr. Israel Nelken (israel.nelken@mail.huji.ac.il).

Materials availability

This study did not generate new unique reagents.

Data and code availability

- Rat licking data have been deposited on Mendeley Data and are publicly available as of the date of publication. DOIs are listed in the [key resources table](#).
- All original code has been deposited on Mendeley Data and is publicly available as of the date of publication. DOIs are listed in the [key resources table](#).
- Any additional information required to reanalyze the data reported in this article is available from the [lead contact](#) upon request.

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AUTHOR CONTRIBUTIONS

Conceptualization, V. G. R., J. W. H. S., and I. N.; methodology, V. G. R., Y. T., J. W. H. S., and I. N.; investigation, V. G. R., Y. T., T. K., J. W. H. S., and I. N.; writing – original draft, V. G. R.; writing – review and editing, V. G. R., J. W. H. S., and I. N.; funding acquisition, J. W. H. S. and I. N.; resources, J. W. H. S. and I. N.; supervision, J. W. H. S. and I. N.

DECLARATION OF INTERESTS

The authors have no competing interests to declare.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

- [KEY RESOURCES TABLE](#)
- [EXPERIMENTAL MODEL AND STUDY PARTICIPANT DETAILS](#)
 - Animals
- [METHOD DETAILS](#)
 - Behavioral setup
 - Training
 - Variable ISI metronome task
- [QUANTIFICATION AND STATISTICAL ANALYSIS](#)
 - Data analysis

- Markovian model – Conceptual description
- Markovian model structure
- Model parameters
- Model fitting

SUPPLEMENTAL INFORMATION

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Rat licking data	This paper	Mendeley Data: https://data.mendeley.com/datasets/5g5scfhmkj/1
Experimental models: organisms/strains		
Rat: Wistar (female)	Chinese University of Hong Kong Animal Facility	N/A
Software and algorithms		
MATLAB analysis scripts + implementation of Markovian models	This paper	Mendeley Data: https://data.mendeley.com/datasets/5g5scfhmkj/1

EXPERIMENTAL MODEL AND STUDY PARTICIPANT DETAILS

Animals

All procedures were performed according to protocols approved by the Animal Research Ethics Subcommittee of the City University of Hong Kong. Eight adult female rats (Wistar; 250-280g) with normal acoustic startle responses were housed in pairs and used in this study. Rats were on a schedule of 5 days of testing (2 sessions/day at least 4 h apart), during which water was a positive reinforcer, followed by 2 days of ad lib water. Water bottles were removed 16 h before the first testing session of the week. During testing, reward amounts were adjusted such that rats received no less than 8 mL per day. If a rat's performance was especially poor, the required amount of water was delivered in the rat's home cage.

METHOD DETAILS

Behavioral setup

The behavioral setup consisted of a custom-built cage with one water spout controlled by a solenoid valve, a speaker, and a white LED placed overhead. A simple transistor circuit detected contacts the rat made with the spout, and a TDT RZ6 real time processor (Tucker Davis Technologies, Florida) was used to detect licks and open the water spout if required. The delay between spout contact and the command being sent to open the spout (after computing whether the lick satisfied the conditions for reward) was measured from within the program based on the timestamps for the two events and was consistently under 3 ms. The TDT processor was controlled using custom code written in RPDsEx, and experiments were run using custom-written Python code in the Spyder environment from a Windows PC. The behavioral box was placed inside an acoustically shielded chamber, and rats were placed into the box one at a time and monitored by the experimenter using a web camera.

Training

Training was conducted in three stages. In all stages of training and testing, rats performed two ~16 min sessions per day. In stage 1, any licks to the water spout were rewarded with a small drop of water, and through this the animals were familiarized with licking the spout for reward. This stage also enabled us to measure the natural lick rate of the rats (roughly 7 Hz; see [Figure S9A](#)). Despite several attempts, we were not successful in training the animals to slow down the rate of their licks. However, rats were able to switch on and off their licking reasonably flexibly.

The second stage of training was a "T-on, T-off" task, which was designed to train rats to 1) associate sound (white noise) with reward availability during the sound on period (T), and 2) break contact with the spout during silence for a minimum amount of time (T) before reward would become available again. Three values of T were tested: 750, 1000, 2000, and 3000 ms. In this task, all licks during "T-on" were rewarded, and any licks during "T-off" were unrewarded and additionally reset the "T-off" period. Thus, for sound (and thereby, reward) to become available again during "T-off," the rat had to avoid touching the spout for at least T seconds. The rats quickly understood this and adjusted their inter-lick intervals (LLIs) to match T ([Figure S9B](#)). Thus, the rats were capable of suppressing their licks, often by biting the spout or moving the head away from the spout, for a flexible amount of time that was clearly stimulus-specific, even if they could not slow down their natural lick rate. A single value for T was selected and presented continuously to the animal during a given session.

In the third and final stage of training, rats were introduced to the metronome task with a longer reward window that was gradually tightened ($\pm 20\%$, 15%, 10% and finally 7.5% of each ISI). Altogether, training lasted roughly 3 weeks, with roughly half of this time spent in the final, third, stage.

Variable ISI metronome task

Each trial in the metronome task consisted of 16 isochronous white noise bursts. Noise bursts were used to strongly drive neural activity in the auditory system, and the number of bursts was chosen to strike a balance between enabling the animal to produce a reliable behavioral response on a given trial, while at the same time challenging the animal to switch quickly to novel tempi on subsequent trials. The inter-stimulus interval (ISI) for each trial was drawn at random from a log-spaced uniform distribution between 0.5 s and 2 s, such that trial ISIs were equally probable in the two octaves of possible ISIs spanned by the experiment. The duration of the white noise burst was 7.5% of the ISI and represented the latter half of the reward time window during which reward was possible. A window of $\pm 7.5\%$ of the ISI was chosen to make the task nearly impossible to solve by simply reacting to beat onsets, since for the slowest interval the window of reward would only be 150 ms following the beat, which is at the lower limit of conditioned reaction times in rats.⁵² To trigger the spout to open and deliver a small drop of water reward, a lick needed to be within $\pm 7.5\%$ of the ISI from a beat onset, and had to be separated from the preceding lick by at least 450 ms, which ensured that licking continuously irrespective of the timing of the sounds would not be rewarded. Each trial in a session lasted between 8 s and 32 s ($16 \times$ ISI) and was separated from the next trial by 4–5 s (drawn randomly from a uniform distribution) of silence. A 1000 ms 5 kHz tone was played as soon as the 16th beat ended to signify the end of the trial. As a further incentive, the size of the water reward was incrementally increased by leaving the spout open for an additional 2 ms following each correct response in a trial and reset to the baseline duration at the start of the next trial. On occasion, rats were unmotivated during a session and would not engage with the spout. During each ~ 16 -min session, rats typically performed ~ 45 – 50 trials before they stopped engaging with the water spout, presumably due to satiation. Between 18 and 23 sessions were collected per animal.

QUANTIFICATION AND STATISTICAL ANALYSIS

Data analysis

Trials containing no licks were discarded from analysis. As described in *Training*, we could not train rats to slow down their natural ~ 7 Hz lick rate, but we were able to train rats to suppress licking for specific time intervals which were indicated by a periodic auditory stimulus. Thus, only the first lick of each lick burst, which needed to be separated from the preceding lick by at least 450 ms, were analyzed because they were considered a reflection of the animal's intention to synchronize with the metronome to receive reward. Burst asynchronies were calculated by subtracting from each burst time its nearest beat onset and dividing the result by the ISI of that trial. Burst asynchronies thus were expressed as fractions of the ISI and ranged between -0.5 and $+0.5$ relative to the nearest sound onset, where an asynchrony of 0 corresponds to the time of a beat. Lick burst asynchronies were binned into phase bins of 0.05 of the ISI. The data shown in [Figure 2](#) therefore reflect the probability of a lick burst in each $0.05 \times$ ISI time bin.

As a control for testing whether rats had found and adopted a strategy that did not require them to adjust their behavior to the auditory metronome, a conservative simulation was performed. The simulation left the temporal structure of licks intact but analyzed the behavior as if it was in response to a different metronome tempo. Simulation ISIs were drawn at random from the same log-uniform distribution over the 0.5 to 2 s range that was used throughout the experiment. When a simulated ISI was longer than the actual ISI for a trial, fewer than 16 beats were analyzed based on the simulation. This simulation was run 100 times with different, randomly drawn simulated ISIs, and the data shown in [Figure 2G](#) compare averaged simulation data with real data truncated where necessary to match the duration of simulation trials. A p -value was calculated for each time bin based on how often its lick burst rate was different from the 100 lick burst rate values produced by the shuffling procedure for that time bin. These p -values were corrected for multiple comparisons using the Benjamini-Hochberg step-up procedure, which sets the rate of false positives to α_{FDR} (here $\alpha_{FDR} = 0.01$) by first sorting the p -values of all the $m = 21$ tests (obtained from the previous step) on H_1, \dots, H_k null hypotheses in ascending order, then finding the largest k such that $p_k \leq \frac{k}{m} \alpha_{FDR}$, and rejecting all null hypotheses H_1, \dots, H_k .

Markovian model – Conceptual description

We define predictive synchronization here as a behavior in which 1) motor responses are temporally locked (potentially only probabilistically) to periodic beats, and 2) the periodic changes in the probability of these motor responses depend on the beat rate. Requiring both of these conditions avoids confounding predictive synchronization with behaviors that are stereotypically locked to the beats (e.g., startle responses or purely reactive responses to beats), or that depend on the beat rate but are not locked to beats (e.g., changes in the rate of randomly timed movements that depend on tempo). Importantly, this more general theoretical construct accommodates a one-to-many beat-to-action correspondence, so long as the timing of changes in the statistical properties of the elicited actions are locked to, but also depend on, the beat rate.

Our approach is therefore based on a state-based (e.g., high probability of beat-related action vs. low probability of beat-related action) view of rhythmic synchronization, noting that the regular one-to-one beat finger tapping that is typical to human behavior is a special case of this state-based formulation. To conceptualize how the model works in practice, let us consider the intuitive case of human one-to-one finger tapping. The stimulus and tap sequence can each be discretized to produce a time series that represents the state of the external stimulus (beat or no beat) and the behavior (tap or no tap, corresponding to the Lick and Pause states in [Figure 3A](#)). Suppose that the time step of the model is 10 ms. A trial in which the metronome rate is 1 Hz would have a beat once every 100 time steps. A human tapping to this metronome would also typically produce a tap once every ~ 100 time steps. A model that assumes a constant tap probability, irrespective of external events, would have a probability of 0.99 of progressing along the Pause branch (because its probability to generate a tap at any time point

is 0.01). Since humans produce single taps, the probability to progress along the Lick state would be 0 (the probability of exiting the initial Lick state would be 1). This model would produce single taps with inter-tap intervals that are widely distributed (having a geometric distribution with a mean of 1 s). However, such a model would be a poor fit to human tapping since human taps are concentrated around beats and occur with an inter-tap intervals of about 1 s.

By allowing the transition probability from no-tap → tap to be extremely low immediately following a beat, but then jump to a larger value at some point during the inter-beat period, it is possible to better capture human behavior. Importantly, the times at which these changes in probability occur reflect whether the process is predictive. For example, if the model posits a jump in tapping probability to occur soon after a beat is heard, independent of beat rate, the model would be interpreted as ‘reactive’ – reflecting the fact that tap times are not sensitive to the expected timing of the next, upcoming beat. On the other hand, if the jump in transition probability occurs at a time point determined by a function of the beat interval, for example, jumping to a high no-tap → tap transition probability after 99% of the beat interval has elapsed, the model would generate tap patterns that are predictive, locking with a near-zero or negative mean asynchrony to the beat for all tempi. Therefore, even in the simple case of human one-to-one finger tapping, the beat rate-dependence of the parameters linking behavior to the external stimulus is the key diagnostic indicator of predictive synchronization.

Markovian model structure

Rat behavior was analyzed at a resolution of 10 ms. The state graph of the model (Figure 3A) illustrates the alternation through time between two behavioral states, described by the two “branches” of the graph: Lick and Pause. Within each branch, each state has two possible transitions: either forward to the next state within the branch, representing an elongation of the current behavioral state, or to the first state of the other branch, representing the end of a lick burst (and the start of a Pause), or the end of a Pause (and the initiation of a lick burst). The branch lengths should be considered as infinite, but in practice rats reached only a finite set of these states, since lick bursts were typically shorter than 1 s (100 states) and breaks could not be longer than 32 s (3200 states, trial duration of the longest trial). For simplicity, we set the maximum duration that the rat could spend in any behavioral state at 10 s (1000 states). The transition probabilities of the model depend on the current state only, and not on past history, but were allowed to vary based on external events in temporal proximity to the current state (e.g., metronome beats and water reward), with details depending on the model. Thus, we consider the external events occurring during a trial as a deterministic sequence that interacts with the alternation of Licks and Pauses by modulating the transition probabilities between them.

The time-dependence of the transition probabilities along the Lick branch of the process is induced by water reward. If a lick burst is initiated within the rewarded window, the lick burst is rewarded. Note that whether a lick burst is rewarded or not cannot be modeled by a probabilistic transition, since the decision of whether or not to reward a burst is deterministic based on the timing of the lick burst. In the water-dependent models, we assume separate sets of transition probabilities for unrewarded and for rewarded lick bursts.

The time-dependence of the transition probabilities along the Pause branch of the process is induced by metronome beats. In the sound-sensitive models, we posited a ‘responsive window’ during which lick burst probability is especially suppressed. We modeled this by assuming two separate sets of transition probabilities along the Pause branch, one used during spontaneous pauses and the other for the responsive pauses. The set of parameters used was determined by the time of the specific state transition relative to the metronome beats. Thus, during a single Pause, transition probabilities could shift from spontaneous to responsive and back. In Figure 3G, this occurs for the marked Pause in the middle of the scheme, which starts before the beginning of the responsive window but extends into it.

The Insensitive model, where all transition probabilities are time-invariant, can generate a wide range of distributions of Lick and Pause durations by setting the transition probabilities appropriately. Indeed, if B is the random variable of lick burst durations, and if the exit probability of going from state n of the Lick branch to the initial Pause state is set to:

$$P(B = n | B \geq n) \quad (\text{Equation 2})$$

(the probability of the lick burst being of length n exactly, given that it is at least n), then the distribution of the duration of lick bursts generated by the model will be that of B . Similarly, the model can generate any distribution of pause durations.

There is nevertheless one important characteristic of the data generated by the model – in the time-invariant case, the durations of successive lick bursts and pauses are statistically independent. In other words, knowing the duration of a lick burst does not change the distribution of the next pause, or of the Lick after that Pause, and so on. This independence property is not necessarily kept in the time-varying case, since external events may induce correlations between the durations of successive Licks and Pauses. Another potential source of small correlations in the data are slight differences in behavior between rats. For example, if one rat tends to overall produce shorter episodes of Licks and Pauses, and another rat tends to produce longer ones, the overall data may show weak correlations between successive Licks and Pauses. In our data, the correlation coefficient between the durations of successive lick bursts and pauses was $r = -0.061$ ($N = 74,279$; see Figure S10). This correlation is very small and likely induced by the small inhomogeneities in the data described above (see Figure S11), and thus we do not consider it as practically important.

Model parameters

We describe here in detail the parametrization of the transition probabilities between process states. The a , b , c , and d parameters that set the responsive window are described fully in the main text (see Equation 1).

In its full generality, the model allows for separate optimization of the exit probability from each process state to the initial state of the other branch (with the continuation probability being its complement). However, this parametrization would require the estimation of thousands of

parameters, resulting in low statistical power to discriminate between models. Therefore, we limited the testing of the models to only a few families of parametric distributions.

For Bursts, we tested the geometric distribution $P(L=n) = p(1-p)^{(n-1)}$ as well as $P(L=n) = np^2(1-p)^{(n-1)}$, which yields a unimodal probability distribution that peaks at one side or the other of $1/p$, and decreases asymptotically like the geometric distribution for large n . Such unimodal distributions could in principle be a better fit to the data than the geometric distribution. Both distributions were parametrized by p , the 'exit probability' (or asymptotic exit probability in the second case) from one branch and into the initial state of the other branch. In both cases, it is possible to compute the transition probabilities along the Lick branch of the model analytically using Equation 2: they are $1-p$ (independent of position along the branch) and $(1-p)^2/[1 - (1-1/n)p]$ for the respective distributions, with the exit probabilities being the respective complements.

For lick burst durations, the geometric distribution was invariably a better fit to the model. In the water-sensitive models, we specified two separate parameters for the lick burst durations, one for the unrewarded and one for the rewarded licks. Thus, lick bursts durations were modeled as having geometric distributions, with rewarded licks having a smaller exit probability at each time point (longer lick bursts) than unrewarded lick bursts (e.g., Figure 5C).

To model pause durations, we had to implement the condition that nominally, pauses had a minimal duration of 450 ms (45 steps of the process). Due to a small number of <450 ms pauses in the data (presumably at the beginning and end of trials), we parametrized the first 45 steps of the Pause branch by a separate, fixed exit probability. After optimization, this exit probability turned out to be indeed small, accounting well for the deadtime in the distribution of pauses. Beyond these initial 45 steps, transitions in the Pause branch could be spontaneous or responsive, depending on the time of the state relative to the last metronome beat. Spontaneous and responsive Pause transitions were parametrized by two separate exit probabilities. Thus, probabilities along the Pause branch of the model could switch seamlessly from one value to the other, in case a Pause that started during the spontaneous window extended into the responsive window, or vice versa. This parametrization resulted in a complex distribution for pause durations, with a 450 ms deadtime of durations that had extremely low probability of occurring, followed by a large jump in probability and a monotonic decrease.

These parametrizations resulted in models that had up to 5 transition probability parameters (exit probabilities for unrewarded and for rewarded Licks; exit probability for the relative deadtime of Pauses; exit probabilities for spontaneous and responsive Pauses). In addition, the sound-sensitive models had either 2 (in the Reactive case) or 4 (in the Predictive case) additional parameters describing the linear dependence of the responsive window on the metronome period. Table S1 schematically summarizes the parameter structure of each of the six models tested. Table S2 fills in this table with the optimized parameters from the main analysis, and Figure 5 in the main text shows these parameters for the 5-group, tempo-resolved model.

Model fitting

To estimate these parameters, all trials were first decoded, with each time bin of each trial assigned as either part of a Lick or Pause (Figure 3B). Given the parameters of the model being fitted, the specific type of behavioral state was determined (unrewarded vs. rewarded Burst, and normal vs. responsive Break). Based on this decoded representation of a trial given a specific model, the transition probabilities for all the transitions that actually occurred in the data were computed. We then summed the logarithms of these probabilities to get the overall log likelihood of a trial given the model. The log-likelihoods were summed over all trials and all rats to give the overall log likelihood of the data given a model with this set of parameters. The maximization of this overall log likelihood was performed in two steps. First, for a given set of responsive window parameters, the transition probability parameters were optimized using the MATLAB routine `fmincon` (MATLAB 2020a-2023a). The step was sufficient for the Insensitive and for the Water sensitive models, which did not have a responsive window. For the sound-sensitive models, the log likelihood map as a function of the four (predictive) or two (reactive) responsive window parameters tended to have an uneven landscape of values, with multiple local maxima. Therefore, for the sound-sensitive models, the transition probabilities were optimized for a grid of possible values of a , b , c , and d parameters. The slope parameters a and c ranged independently from 0 to 1 (fractions of the ISI) in increments of 0.1 for the Predictive models, and were set to 0 for the Reactive models. The shift parameter b ranged from -0.5 to 0.5 s in 0.1 s increments, and d ranged from -1 to 1 s in 0.1 s increments. The parameter values that had the maximum likelihood over this grid were selected for the optimal model.

To compare the goodness of fit of the six different models, we used log likelihood tests for nested models. A nesting occurs when the parameters of one model can be reduced to those of another by setting some of them to predetermined values (see Table S1 for the nesting relationships between the models considered here). Importantly, the log likelihood of nested models can be compared: the log likelihood of the richer model will always be larger than that of the reduced model. Under the null hypothesis that the data are independent of the additional parameters, $2 \cdot \Delta LL \sim \chi^2$ (df), where df is the number of additional free parameters of the richer model⁵³; we only compare nested models here.