Rhythmic coordination of hippocampal-prefrontal ensembles for odor-place associative memory and decision making

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ABSTRACT

Memory-guided decision making involves long-range coordination across sensory and cognitive brain networks, with key roles for the hippocampus and prefrontal cortex (PFC). To investigate coordination mechanisms that mediate sensory-cued decision making based on learned associations, we monitored activity in hippocampus (CA1), PFC, and olfactory bulb in rats performing an odor-place associative memory and decision task on a T-maze. During odor sampling, the beta (15-30 Hz) and respiratory (7-8 Hz) rhythms (RR) were prominent and coherent across the three regions, with beta specifically linked to fast decisions. Single neurons and ensembles in both CA1 and PFC encoded and predicted animals' upcoming choices, with choice-encoding dynamics linked specifically with beta rhythm coordination. Beta phase modulation of CA1 interneuron activity was linked to accurate decisions, suggesting a mechanism for enabling temporal coordination. Our findings indicate that beta rhythm coordination within the hippocampal-prefrontal network supports utilization of odor cues for memory-guided decision making.

KEYWORDS

Hippocampus; Prefrontal cortex; Beta oscillations; Respiratory rhythm; Phase locking; Decision making; Olfactory Bulb

INTRODUCTION

The ability to recall associations from memory and use them to guide behavior is a key aspect of cognition across species. Animals can associate sensory cues in the environment with rewarding and noxious experiences and utilize these cues for adaptive behavior. Memory-guided decision making demonstrates the brain's remarkable ability to link familiar cues with actions and beneficial outcomes, but little is known about the mechanisms responsible for this cognitive function.

Neurons that encode learned associations and reflect upcoming choice behavior have been reported in multiple regions in different sensory modalities[1-14]. However, sensory cued decision-making based on learned associations necessarily involves a brain-wide network that links primary sensory areas, the medial temporal lobe, and higher cortical areas involved in executive function. Numerous studies have highlighted the significance of the hippocampus and prefrontal cortex (PFC) in cognitive processing related to memory and decision making[15-19]. Both regions are known to encode behaviorally relevant cues and task features[2-4,20-22], and have been shown to play key roles in memory recall[23-26]. Notably, coordinated activity between the hippocampus and PFC, supported by bidirectional anatomical connections[27-29], has been shown to be critical for learning and memory-guided behavior[30-35]. Therefore, we focused on the coordinated interactions between hippocampus and PFC as a potential key mechanism through which learned associations are recalled and translated into memory-guided decisions.

Several studies have shown that rhythmic network oscillations in the local field potential (LFP) are involved in long-range interactions between the hippocampus and PFC[30,36-40]. In particular, phase coherence in distinct frequency bands across this network has been suggested as a mechanism for network coordination underlying mnemonic functions. Notably, hippocampal-prefrontal coherence in the theta rhythm (6-12 Hz) plays a role in spatial working memory and acquisition of spatial tasks[37,38,41,42]. However, whether similar mechanisms of

coordination between hippocampus and PFC underlie decision making based on sensory cued

associations is unclear.

Rodents rely heavily on odor cues for navigation and foraging, so odor memories are

highly salient and robust[43-46], making olfactory memory tasks ideally suited for studying memory-

guided decision making. Previous studies using odor memory tasks have found prominent beta

(15-30 Hz) oscillations in olfactory regions and the medial temporal lobe during cue sampling,

suggesting that the beta rhythm acts as a potential mode of long-range communication for

olfactory information processing[5,47-50]. In addition to the beta rhythm, the respiratory rhythm (RR;

7-8 Hz), driven by the animal's breathing cycle, is also prominent in the hippocampus during

mnemonic processing of odor stimuli[51-55]. However, not much is known about the roles of these

rhythms in coordinating activity in the hippocampal-prefrontal network during odor-cued decision

making.

To elucidate these mechanisms, we employed an odor-place association task in which

rats were required to choose the correct trajectory on a T-maze by recalling and utilizing familiar

associations between odor cues and reward locations. While rats were performing the task, we

recorded simultaneously from the hippocampus and PFC. Given the involvement of both of

these regions in odor-memory tasks[34,56-62], and the role of hippocampal-prefrontal networks in

memory-guided behavior[23,24,26,63-65], we hypothesized that rhythmic activity in this network may

govern the cellular representation of odor-cued decisions underlying behavioral choices. We

also monitored LFP activity in the olfactory bulb (OB) in addition to CA1 and PFC, for robust

samplings of previously reported olfactory rhythms such as beta and RR, which have been

implicated in cognitive processing of olfactory stimuli[66,67]. Our results point to a specific role of

beta rhythms in coordinating the olfactory-hippocampal-prefrontal network for utilizing learned

odor-place associations to inform decisions, and shed light on the cellular and network

mechanisms underlying this process.

RESULTS

Odor-place associative memory and decision-making task

The odor-cued spatial associative memory task required rats to sniff at an odor port

where one of two possible odors was presented using a calibrated olfactometer (see **Methods**).

The rats were required to choose the correct associated reward arm on the T-maze based on

the sampled odor identity, where they would receive a reward of evaporated milk (**Fig. 1a**).

Rats were habituated to the maze and pre-trained on the task before surgical implant of

a tetrode microdrive array for recording neural data. Following post-operative recovery and

during electrophysiological recording, animals maintained a high level of performance on the

task, indicating accurate decision making based on cued recall of odor-place associations (**Fig.**

1b, n = 8 rats, 77.0% ± 1.3%, mean ± s.e.m.). Rats were required to hold their nose in the odor

port for a minimum of 0.50 seconds on each trial, but could continue sniffing the odor for any

length of time after the minimum threshold was reached. The odor was continuously dispensed

for the entire duration of time that the rat held its nose in the odor port and was only turned off

once the rat disengaged from the odor-port. The average odor-sampling duration before odor

port disengagement and odor offset was 0.82 ± 0.02 seconds (mean ± s.e.m. across sessions),

and this duration was similar between correct and incorrect trials (**Fig. 1c**; signed-rank test, p =

0.71, distribution for all trials shown in **Supplementary Fig. 1a**). The animals' average velocity

during the task showed a decrease in speed from the pre-odor period to the odor sampling

period in the odor port, followed by an increase in speed after they left the odor port to run to the

reward location (**Supplementary Fig. 1b-c**). We observed rapid movement away from the odor-

port only after odor-port disengagement (**Supplementary Fig. 1d**). In two animals, a

thermocouple was implanted in the nasal cavity to measure the sniff rhythm (see **Methods**).

There was a small but significant increase in sniff rate during the odor sampling period (7.1 ±

0.39 Hz, mean ± s.e.m.) compared to time matched pre-odor periods (6.2 ± 0.29 Hz, mean ±

s.e.m.) (**Supplementary Fig. 1e**).

Notably, we observed that on a majority of trials (95.4% ± 0.12%), the animals' turn

direction away from the odor port matched the direction of the T-maze reward arm that they

would ultimately choose on that trial. This behavioral phenomenon was not required for

successful performance of the task, and it occurred regardless of whether the trial was correct

or incorrect (**Fig. 1d**; binomial tests, correct trials: $p = 0$; incorrect trials: p = 1.4e-108). This

observation indicates that the rats recall the odor-place association and choose the reward

location for each trial *during* the odor sampling period, before exiting the odor port to run toward

reward. The time of disengagement from the odor port thus provides a trial-by-trial estimate of

the moment at which the animal executes the decision. The odor sampling period corresponds

to odor-cued recall of the learned association and priming of the subsequent decision to turn

toward the reward location, with behavioral report of the decision occurring at odor port offset.

We therefore termed this odor sampling period as "the decision-making period," since it

provides a temporal window between odor onset and odor port exit to investigate mechanisms

underlying odor-cued decision making.

110   Beta rhythms support decision making based on odor-place associations

We therefore focused on the decision-making period and first sought to determine the

network dynamics that underlie coordination of brain regions during this period. We used a

tetrode microdrive array to record local field potentials (LFPs) and single units from the dorsal

CA1 region of the hippocampus, the prelimbic region of the prefrontal cortex (PFC, primarily

prelimbic area), and the olfactory bulb (OB, only LFP) in rats as they performed the odor-place

association task (see **Methods**; **Supplementary Fig. 2a-b**). The thermocouple signal and LFP

traces from CA1, PFC, and OB from an example trial are shown in **Fig. 2a**, along with the same

LFP signals filtered in the 15-30 Hz band (additional example shown in **Supplementary Fig.**

2c).

We observed a strong increase in power in the beta band (15-30 Hz) during this

decision-making period compared to a time-matched pre-odor period across all three regions

(**Fig. 2b**; **Supplementary Fig. 2d-e**). Similar increases in beta power during odor discrimination

tasks have been reported previously in OB, CA1, and lateral entorhinal cortex[5,47-49]. The

respiratory rhythm (RR, 7-8 Hz) was also prominent in the LFP in all three regions[51,53], showing

an increase in power in PFC and OB during odor-sampling compared to time-matched pre-odor

periods (**Fig. 2b; Supplementary Fig. 2d,f**). This rhythm, which corresponds to the respiration

rate during odor sampling, has previously been shown to be physiologically and mechanistically

distinct from the 6-12 Hz hippocampal theta rhythm[51,53], although there is overlap between the

two frequency bands. Following odor port disengagement and the initiation of running down the

track, we observed a small shift in the dominant LFP frequency from RR to the theta band in

CA1 and PFC, reflecting the change in behavioral state (**Supplementary Fig. 2g**).

During the decision-making period, we found phase-amplitude coupling between beta

and RR in all three regions, consistent with previous findings[53] (**Supplementary Fig. 2h),** and

suggesting a mechanistic relationship between the two rhythms. Despite this relationship,

previous literature shows that the two rhythms are differentially generated and maintained in the

olfactory system and hippocampus and appear to serve different functions in olfactory

processing[66-69]. This indicates that the beta rhythm is not merely a harmonic of RR despite

apparently similar modulations in amplitude during this task.

Odor sampling during the decision-making period thus drives prominent increases in the

beta and RR rhythms in OB, CA1 and PFC. We next examined LFP coherence and its temporal

dynamics in relationship to behavior. The hippocampal-prefrontal (CA1-PFC) network exhibited

prominent and consistent coherence at the beta frequency band during odor sampling, prior to

the decision execution at odor-port offset (**Fig. 2c**). This coherence was specific to the odor-

sampling period: it significantly increased compared to time-matched pre-odor periods (**Fig. 2d,**

sign-rank test, p = 6.7e-6), and diminished shortly after the rat exited the odor port, once the

decision had been made (**Fig. 2c**). Additionally, we observed coherence in the RR band in the

CA1-PFC circuit, although there was no significant change between pre-odor and odor-sampling

periods (**Fig. 2d,** signed-rank test, *p* = 0.36). During running, after the decision-making period,

the prominent low frequency RR coherence shifted to be slightly higher and centered on the

canonical theta band (6-12 Hz), similar to what was observed in the LFP power spectrum

(**Supplementary Fig. 3a**). Beta and RR coherence were also observed between the CA1-OB

and PFC-OB regions during odor sampling periods, with similar temporal dynamics as CA1-PFC

beta coherence (**Supplementary Fig. 3b-c**).

To directly examine the influence of rhythmic coordination on task dynamics, we asked

whether the animal's decision latency, indicated by odor port exit time, was linked to the degree

of network coordination. A significant negative correlation between the decision latency time and

CA1-PFC beta coherence indicated that a higher degree of beta coordination in the network is

associated with faster decisions, whereas there was no significant correlation between RR

coherence and decision latency time (**Fig. 2e,** beta: r = -0.54, p = 4.4e-4; RR: r = 0.03, p =

0.87). Similarly, CA1-OB beta coherence, but not RR coherence, was also correlated with

decision latency (**Supplementary Fig. 3d**), but there was no significant relationship between

decision latency and PFC-OB coherence in either frequency band (**Supplementary Fig. 3e**).

To control for the possibility that elevated beta coherence during the decision-making

period was simply a reflection of passive movement preparation, as has been observed in

sensorimotor cortex[70,71], we compared CA1-PFC beta coherence during the last 500ms of the

decision-making period with the 500ms just prior to reward well exit. We confirmed that beta

coherence observed during the decision-making period was significantly higher than coherence

at the reward well. (**Fig. 2f,** signed-rank test, p = 1.2e-7). In an additional control, we also

confirmed that this elevated beta coherence was specifically seen during odor-cued decision

making and was not present in sessions in which only air was presented at the odor-port (see

Methods). In these air-only sessions, reward was given on random trials at the reward

locations, even though no odors were presented. RR coherence was unchanged between odor-

and air-cued sessions, but beta coherence was significantly lower during air-cued sessions

(**Supplementary Fig. 3f-g**).

Although we found a strong relationship between beta coherence in the CA1-PFC

network and decision latency, we did not find a direct relationship between the strength of beta

coherence or RR coherence to correct performance on the task. There was no significant

change in the level of coherence in the CA1-PFC network in either frequency band between

correct and incorrect trials (**Fig. 2g,** signed-rank tests; beta: p = 0.38; RR: p = 0.81). This

pattern was true of CA1-OB coherence (**Supplementary Fig. 3h**), as well as PFC-OB

coherence (**Supplementary Fig. 3i**). Additionally, although beta power was higher on correct

trials compared to incorrect trials in PFC, this was not true of either CA1 or OB (**Fig. 2h** (top

row), signed rank test; CA1: p = 0.08; PFC: p = 9.3e-4; **Supplementary 3j**). RR power was

unchanged between correct and incorrect trials in all three regions (**Fig. 2h** (bottom row),

bootstrap test; CA1: p = 0.26; PFC: p = 0.16; **Supplementary 3j**). Therefore, while beta

coherence in the CA1-PFC network may facilitate quicker decision making, the strength of

oscillatory coordination in the network may not directly or inherently enable a correct decision

suggesting that oscillatory modulation of cellular activity may instead play a role.

We were curious if these beta rhythm dynamics were limited to the odor sampling

location on the maze. Indeed, CA1-PFC network beta power and coherence were clearly

isolated to the region near the odor port (**Fig. 2i**). Finally, since hippocampal sharp-wave ripples

(SWRs) have been proposed as a mechanism for memory retrieval, decision making, and

planning in some tasks[13,72-74], we also investigated the occurrence of SWRs during our task.

SWR events occurred frequently at the two reward locations, as expected[75]. However, a distinct

lack of SWR events at the odor port (**Figs. 2i** and **2j**; signed-rank test, *p* = 1.1e-7) suggests that

SWR replay is unlikely to play a direct role in decision making based on recalled associative

memories for this well-learned task; rather, the beta rhythm appears to be a primary

coordination mechanism for this function. Together, these results suggest that the beta rhythm

specifically plays a principal role in odor-cued decision making in this task, while RR may play a

more passive role in organizing sensory information transfer during cue utilization.

Single neurons in CA1 and PFC exhibit choice selectivity during decision-making period

In addition to LFP, we recorded single units from hippocampal CA1 (n = 1,309 units) and

PFC (n = 717 units) (distribution of neurons across animals shown in **Supplementary Table 1**).

Units that were active during run sessions were categorized into pyramidal cells and

interneurons based on firing rate and spike width (see **Methods,** CA1: 87% pyramidal, 13%

interneurons; PFC: 87% pyramidal, 13% interneurons). Pyramidal cells were then further

categorized as task-responsive or task-unresponsive based on whether they exhibited

significant changes in firing rate during odor sampling (see **Methods**; n = 125 task-responsive

CA1 cells, n = 157 task-responsive PFC cells). We observed an overall increase in spiking

during the odor sampling period in the task-responsive cell population, suggesting that the

majority of these cells increase their firing rate during this period (**Supplementary Fig. 4a**).

Interestingly, however, there was an overall decrease in spiking in the average peri-stimulus

time histograms when pooling all spikes from all cells during the odor-sampling period

(**Supplementary Fig. 4b**), suggesting a decrease in overall responsiveness in CA1 and PFC

networks during odor sampling. Additionally, we confirmed that task responsive neurons were

not simply modulated by the animals' decrease in speed at the odor-port by comparing firing

rates during odor sampling to firing rates during reward consumption, when speed was also low.

We found task-responsive cells' firing rates were significantly higher at the odor port than at the

reward wells (**Supplementary Fig. 4c**).

A subset of task-responsive cells was selective for specific choices, based on the

identity of the odor and the associated choice. Selectivity was calculated by generating a

selectivity index (SI), in which the difference between the average firing rate response to each

odor on correct trials was divided by the sum of the two responses, giving a value between -1

and 1 (see **Methods**). To determine significance, the SI value for each cell was compared to a

distribution of SIs generated by shuffling the odor identities across trials (n = 42 CA1 selective

cells, n = 49 PFC selective cells) (**Figs. 3a** and **3f**). Although the number of selective cells that

we observed was relatively low, these numbers were consistent with other studies examining

single unit responses to odor stimuli in these regions[8,76,77].

Peri-stimulus time histograms and raster plots aligned to decision time for two example

selective cells for CA1 and PFC are shown in **Figs. 3b** and **3g** respectively. Notably, we found

that on incorrect trials, selective cells often exhibited responses to the two odors that were

opposite to the responses on correct trials. (Examples shown in **Figs. 3c** and **3h**). We found

that this phenomenon held true across the population of selective cells, such that overall, the

SIs on correct trials were anti-correlated with the SIs on incorrect trials (**Figs. 3d-e** and **3i-j**).

Note that since there are only two possible choices on the task, the behavioral response on an

incorrect trial is identical to that of a correct trial of the opposite odor. The fact that the neural

responses on trials with identical behavioral responses are similar indicates that selective cells

are not simply coding the odor identity but are instead responsive to the animal's memory-

guided decision and upcoming behavioral choice. In contrast, selectivity to the odor identity

alone would result in similar responses to a given odor regardless of the upcoming behavior or

the ultimate trial outcome. We therefore termed these cells choice-selective cells. This pattern

did not persist within the population of neurons that were task-responsive but did not meet the

selectivity threshold (**Supplementary Fig. 4d-e**). Histograms showing distribution of absolute

selectivity indices between selective and nonselective cells are shown in **Supplementary 4f.**

Putative interneurons were also divided into task-responsive and task-unresponsive,

using the same criteria as for putative pyramidal cells (**Supplementary Fig. 4g**).

Supplementary Fig. 4h-i shows interneuron odor selectivity indices and response properties.

For CA1 interneurons, the selectivity response was similar to that of pyramidal cells. PFC

interneurons' SIs on correct and incorrect trials were not anti-correlated, although there were

very few selective PFC interneurons overall.

Neural ensemble responses during decision making are governed by beta coordination

and predict the upcoming choice

We next examined how ensemble dynamics underlie the neural representation of

decisions informed by odor-cued recall. We considered all cells that were task-responsive

(regardless of the significance of SI for individual cells) for the ensemble analyses. For the

population of task-responsive cells, we found that the distribution of the peak response times in

both CA1 and PFC tiled the entire decision time window (**Fig. 4a**). Using the population

differential index (PDI) as a measure of population response discriminability (see **Methods**), as

described previously[5], we found that distinct representations for the two possible choices

emerged gradually in the neural population during the decision-making time period (**Fig. 4b**).

Briefly, for this analysis, all task-responsive cells were pooled across animals and days into a

single population. Mean firing rates were calculated in 100ms bins to obtain population vectors

(PVs) for each of the two odors, and at each time bin the correlation coefficient between the two

PVs was calculated. This correlation coefficient was subtracted from 1 to obtain the PDI, such

that PDI = 1 indicates that the population responses for the two odors are completely distinct,

whereas PDI = 0 indicates that the responses are identical. Chance-level PDI was computed by

shuffling the odor identities across trials and creating a null distribution.

To determine when this discriminability emerged in the CA1 or PFC ensembles, we

performed a bootstrap test, in which a subset of 50 neurons from each region was randomly

sampled with replacement to use for the PDI calculation. The timepoint at which the population

responses to the odors were considered significantly distinct from each other was defined as the

first timepoint at which the real PDI surpassed the 95% confidence interval of the null (shuffled)

distribution. This procedure was repeated 500 times to generate a distribution of discrimination

times for each region, aligned to odor port disengagement. These bootstrapped distributions

were compared, which suggested that discriminability in the CA1 and PFC ensembles emerged

simultaneously (**Fig. 4c,** CA1: median = 0.19 seconds prior to odor-port disengagement,

interquartile range = 0.06; PFC: median = 0.23 seconds prior to odor-port disengagement,

interquartile range = 0.06; bootstrap test, p = 0.31).

We were next interested in whether the timing of neural discrimination for CA1 and PFC

ensembles on each trial (determined as the time of peak PDI discrimination value) was related

to the decision latency. We determined the timing of peak PV discrimination in each region on

individual trials by comparing the task-responsive PVs on each trial to the average PV on trials

with the opposite odor. Trials in which fewer than 3 total task-responsive neurons in the region

were active were excluded, since at least three datapoints are needed to calculate a meaningful

correlation between PVs. On individual trials, the timing of peak discrimination for both CA1 and

PFC ensembles had small but significant correlations with the decision latency (**Fig. 4d,** CA1: n

= 2241 trials, r = 0.09, p = 4.1e-5; PFC: n = 2087 trials, r = 0.06, p = 0.01; individual trial rasters

shown in **Supplementary Fig. 4j**). This implies a temporal link between the emergence of the

decision in the CA1 and PFC neural populations, and the moment when the animal begins to

execute a behavioral response.

We next asked whether the timing of this neural ensemble discriminability between the

two choices was related to beta coordination in the network on each trial. Indeed, we found that

the timing of peak CA1 PV discriminability on individual trials was weakly but significantly anti-

correlated with the strength of CA1-PFC beta coherence, such that high CA1-PFC coherence

trials had an earlier PV divergence latency and therefore earlier neural discrimination; however,

no significant correlation was seen for PFC PV divergence time. (**Fig. 4e**, CA1: r = -0.12, p =

2.1e-8; PFC: r = -0.03, p = 0.09). Furthermore, we found that the timing of peak beta coherence

on each trial was also weakly but significantly correlated with the timing of peak PV

discriminability, in both CA1 and PFC (**Supplementary Fig. 4k**, CA1: r = 0.05, p = 0.02, PFC: r

= 0.04, p = 0.04), further suggesting a temporal relationship between beta coherence in the

CA1-PFC network and coding of the choice by neural ensembles.

To determine whether the animal's upcoming behavior could indeed be predicted by

neural ensembles before the decision was executed, we trained a generalized linear model

(GLM) to predict the animal's choice based on ensemble activity during the decision-making

period (See **Methods**). We performed this analysis using task-responsive putative pyramidal

cells and found that reward choice could be accurately predicted 0.1 seconds prior to odor port

disengagement by CA1 ensembles, and 0.3 seconds prior by PFC ensembles (**Fig. 4f**).

Additionally, we performed the same analysis, but included both task-responsive pyramidal and

interneurons in the ensembles. In this case, we found an improvement in prediction for CA1

ensembles: reward prediction was now accurate starting earlier, at 0.2 seconds prior to decision

execution. Prediction by PFC ensembles remained the same. (**Fig. 4g**). To control for the

possibility that inclusion of interneurons improved prediction latency for CA1 simply due to the

larger number of cells in the training set, we performed this analysis again by resampling the

pyramidal cells to match the total number of pyramidal cells plus interneurons used in **Fig. 4g.**

In this control analysis, we found that the choice could again only be predicted at 0.1 seconds

prior to the decision execution, the same as what we observed with the original sample of

pyramidal cells. These results confirm that the animals utilize the recalled odor-place

association and make a spatial choice during this odor-sampling period, which is reflected in the

activity of task-responsive neural ensembles. Further, beta coordination in the CA1-PFC

network is linked to the neural activity dynamics underlying this memory-guided decision

process.

To investigate whether there was evidence of coordination between ensembles in CA1

and PFC, we wanted to determine whether the spiking of neuronal ensembles in the two regions

were temporally linked[78,79]. In order do this, we computed the Z-scored cross-correlation for all

CA1-PFC pairs of task-responsive neurons (**Fig. 4h**). Interestingly, we found that the distribution

of the peaks of the cross-correlations for pairs of putative pyramidal cells (n = 603 pairs) was

bimodal, with a peak at -28.5ms and another at 13.3ms. This points to potential bi-directional

spike-time coordination between the pyramidal ensembles in the two regions. Since we also

found task-responsive interneurons that contributed to prediction of upcoming choice, we

hypothesized that inter-regional coordination may also be shaped by interneuron activity. To

examine temporal relationships between interneurons, we performed the same cross-correlation

procedure for all CA1-PFC pairs of task-responsive interneurons (n = 85 pairs), as well as pairs

of CA1 interneurons and PFC pyramidal cells (n = 462 pairs), and vice versa (n = 130 pairs).

We found a prominent peak at 0ms for CA1-PFC interneuron pairs, as well as CA1 pyramidal

cell - PFC interneuron pairs. Additionally, we found a significant 9.5ms lag in the CA1

interneuron- PFC pyramidal cell cross-correlation peak distribution. These results suggest

temporal relationships between these populations, and especially that CA1 interneuron activity

may have a role in sculpting PFC task-responsive ensembles, further suggesting coordination

between the two regions during cue-processing and decision-making.

CA1 and PFC cells phase lock to beta and respiratory rhythms during decision making

We next asked if there was any relationship between oscillatory phase modulation of

cells and decision accuracy. Within the population of task-responsive cells in both CA1 and PFC

we found a fraction of cells that were phase locked to the beta rhythm during the decision-

making period (see **Methods**; CA1: n = 36, 28.8%; PFC: n = 17, 10.8%). Spike-phase

histograms for two example beta-phase locked cells are shown in **Fig. 5a** (Rayleigh Z test, CA1:

n = 242 spikes, z = 15.4, p = 1.5e-7; PFC: n = 99 spikes, z = 4.9, p = 0.007). We also found

that many cells in the task-responsive populations were strongly phase locked to RR (CA1: n =

112, 89.6%; PFC: n = 60, 38.2%). Examples for two of these cells are shown in **Supplementary**

Fig. 5a. For both beta and RR, there was a significant non-uniformity in beta phase-preference

across cells in CA1, and nonuniformity in only beta-phase preference for PFC populations (**Fig.**

5b, Rayleigh Z test; CA1: z =7.88, p = 3.4e-4; PFC: z = 4.9, p = 0.007. **Supplementary Fig.**

5b). The preferred phases of the two cell populations were distinct for both regions (**Fig. 5b,**

Watson-Williams test, *p* < 0.001, **Supplementary Fig. 5b**).

Since our results so far suggested that the beta rhythm may have more relevance to

decision latency and ensemble coordination than RR, we next asked whether phase locking to

the beta rhythm was indicative of accurate decision making. To do this, we compared Rayleigh

Z scores, a measure of non-uniformity in the spike-phase distribution, on correct versus

incorrect trials for significantly phase-locked cells. For each phase-locked cell, we calculated the

Rayleigh Z score for the spike-phase distribution on correct trials for incorrect trials separately

and compared these two paired distributions. We found that in both CA1 and PFC, cells that

were phase-locked to the local beta rhythm exhibited a lower Rayleigh Z on incorrect trials.

There was no significant effect for cross-regional modulation however (**Fig. 5c**, signed-rank

tests, CA1-CA1: n = 28, p = 0.03; PFC-PFC: n = 8, p = 0.007; CA1-PFC: n = 18, p = 0.39; PFC-

CA1: n = 12, p = 0.20). This suggests that local spiking modulation by the beta rhythm in CA1

and PFC can potentially play a role in supporting accurate utilization of odor-place associations

for making decisions. CA1 cells that were phase-locked by local CA1 RR also showed a slight

but significant decrease in modulation on incorrect trials, but we found no change in modulation

strength for locally phase locked PFC cells, nor for cross regional RR phase modulation in either

population between correct and incorrect trials (**Fig. 5d**, signed-rank tests, CA1-CA1: n = 103

cells, p = 0.04; PFC-PFC: n = 35 cells, p = 0.38; CA1-PFC: n = 85 cells, p = 0.26; PFC-CA1: n =

49 cells, p = 0.30). Note that the LFP and spiking analyses found stronger evidence that beta

coordination is related to task performance (**Figs. 2, 4, 5c**), even though a higher percentage of

cells in both regions were phase locked to RR (**Fig. 5e**, z-test for proportions, CA1: p = 6.8e-23;

PFC: p = 8.8e-9) and this modulation was much stronger for RR compared to beta

(**Supplementary Fig. 5c**). Additionally, in both CA1 and PFC, the proportion of cells that were

phase locked to both beta *and* RR was no different than chance, given the percentages of cells

that were modulated by either rhythm (**Supplementary Fig. 5d**). This suggests that the two

rhythms simultaneously modulate slightly different populations of cells, supporting the

interpretation that the two rhythms play separate, though cooperative, roles in memory-guided

decision making.

Are cells that are modulated by beta the same population of cells that code for the

upcoming decision? To test this, we compared the number of pyramidal cells that were both

choice-selective *and* phase-locked (within and across regions) to the fraction that would be

expected by chance, given the total percentages of cells that are choice-selective or phase-

locked. Interestingly, we found that the number of cells that met both criteria was no different

than chance for either CA1 or PFC (**Fig. 5f**, binomial tests; CA1: p = 0.097; PFC: p = 0.17). We

found similar results for RR modulation (**Supplementary Fig. 5e**). It should be noted that since

such a large majority (~90%) of neurons in CA1 were significantly phase locked to RR, it is

unsurprising that almost all the choice-selective cells were phase locked to this rhythm.

However, this result indicates that the choice-selective cells were no more or less likely than

non-selective cells to phase lock to RR. Together, these results suggest that, surprisingly, the

putative pyramidal neural ensembles that code for the primary task parameter of odor-cued

associative decisions may not be driven directly by the beta rhythm, with relatively low

prevalence of beta phase modulation, despite the strong relationship we observed between beta

oscillations, choice-selective ensemble activity and memory-guided decision latency (**Figs. 2,**

4).

We therefore examined the role of beta oscillations in coordinating the activity of

interneurons in the CA1-PFC network. Indeed, we found high prevalence of beta phase

modulation of CA1 interneurons. Of the 102 interneurons in CA1 that were active during the

decision period, 44 (43.1%) were phase-locked to the local CA1 beta rhythm, and 25 (24.5%)

were phase-locked cross-regionally to the PFC beta rhythm. Phase preference among the

neurons in both groups was strongly non-uniform and unimodal (**Fig. 5g**), indicating local- and

cross-regional coordination of CA1 interneurons is governed by beta in a strongly phase-

dependent manner. In contrast, very few of the 37 PFC interneurons were phase-locked to beta,

both locally (3 units, 8.1%) and cross-regionally (1 unit, 2.7%).

Local and cross-regional beta phase modulation of CA1 interneurons was lower on

incorrect compared to correct trials (**Fig. 5h,** signed-rank tests, CA1-CA1: p = 8.2e-9; CA1-PFC:

p = 1.2e-5), suggesting that entrainment of CA1 interneurons to the network-wide beta rhythm is

linked to task performance. About half of the CA1 interneurons that were choice-selective were

also beta phase-locked, although this number was not different than what would be expected by

chance (**Fig. 5i,** binomial tests; CA1: p = 0.11; PFC: p = 0.20), similar to what we observed in

the population of putative pyramidal cells. Our results suggest, therefore, that CA1 interneuron

activity is strongly governed by the beta rhythm locally, as well as in a coordinated manner with

PFC. This also aligns with the finding of temporal relationships in cross-correlations between

CA1 interneurons and PFC pyramidal cells and interneurons (**Fig. 4h**). Beta modulation of

interneurons may thus constrain and coordinate network activity, and may play a role in

sculpting pyramidal cell ensembles in local circuits to enable processing of odor-cued

associations for translation to decisions.

Representations of choice and space are maintained independently during delay period

Finally, we investigated if there was any relationship between the activity of CA1 and

PFC ensembles during the odor-cued decision-making period and their spatial activity on the

maze as the animals ran through the delay period on the central and side arms toward reward.

We examined units from sessions in which animals traversed a long T-maze track (see

Methods, 26 sessions from 6 rats) in order to assess spatial firing characteristics. A large

fraction of cells in CA1 and PFC exhibited spatial activity on the maze (see **Methods** for details

on spatial parameters, n = 344 out of 585 CA1 cells; n = 159 out of 288 PFC cells had fields on

the track), including units that were both task-responsive (choice selective and non-selective)

and task-unresponsive (**Figs. 6a, 6b**; examples of CA1 and PFC choice-selective cells with

spatial fields in **Fig. 6a,** examples of CA1 and PFC task-responsive but non-selective cells with

spatial fields shown in **Supplementary Fig. 6a**).

Cells that were task-responsive were more likely to have spatial fields on the track (odor

sampling periods were excluded in spatial responses, see **Methods**), compared to cells that

were not responsive during the odor sampling period (**Fig. 6b**, binomial test, CA1: p=0.029;

PFC: p=2.7e-5). Additionally, for both CA1 and PFC neurons, we found that the firing rate

during odor sampling was correlated with firing rate during running (**Fig. 6c,** CA1: r = 0.39, p =

3.0e-37; PFC: r = 0.68, p = 1.2e-62), and task-responsive cells had higher firing rates overall

(**Supplementary Fig. 6b**), suggesting a possible relationship between cell activity during

decision making and maintenance of the decision during the spatial delay. To examine this

question further, we asked whether the spatial fields in either CA1 or PFC exhibited different

characteristics based on whether they were responsive during the decision-making period.

Surprisingly however, we found no difference in field width (**Fig. 6d,** rank-sum tests, CA1: p =

0.15; PFC: p = 0.92), field peak rate (**Supplementary Fig. 6c**), or field sparsity

(**Supplementary Fig. 6d**) between cells that were task-responsive and task-unresponsive in

either region.

Further, we also examined trajectory selectivity as animals ran through the central arm

and on the side arms toward reward (examples of trajectory selective firing shown in **Fig. 6a,**

second row). Trajectory selectivity was defined by comparing spatial tuning curves of cells on

right versus left trajectories and calculating a selectivity index analogous to the choice selectivity

index during the decision-making period (see **Methods**). Interestingly, although trajectory-

selective cells were significantly more likely than trajectory-nonselective cells to respond in the

decision-making period (**Supplementary Fig. 6e**), there was no relationship between the

preferred trajectory during run periods and preferred choice during the odor-cued decision-

making period (**Fig. 6e,** rank sum test CA1: p = 0.26; PFC: p = 0.20)**.** Thus, although CA1 and

PFC cells that were task responsive had higher firing rates and therefore higher engagement

while traversing trajectories on the maze, there was no clear relationship between choice

selectivity and trajectory selectivity in either CA1 or PFC.

To confirm this result, we sought to determine whether choice selective neuronal activity

in the population during decision making persisted into the following run period. To examine

this, the linearized T-maze was divided into 5 equally spaced quintiles and a Bayesian Classifier

trained on odor period activity was used to decode the choice identity from the ensemble activity

during run at each spatial quintile (see **Methods**; similar results were seen for spatial quartiles).

We found that choice identity could be decoded at the first quintile of track, nearest to the odor

port, but decoding accuracy diminished to chance level thereafter (**Fig. 6g**). In contrast, the

animal's upcoming behavioral choice could be accurately decoded at all periods along the

trajectory if instead the spatially active ensembles in each respective spatial quintile was used

as the training set (**Fig. 6h**). This suggests that the choice selectivity that emerges in ensembles

during odor sampling (**Fig. 4**) persists transiently for a short period past the decision point, but

that separate ensembles maintain choice-related information as animals traverse the spatial

trajectory, possibly corresponding to theta oscillations during run (**Supplementary 2g**). This is

further supported by the fact that, at least for CA1, choice-selective ensemble firing rate is

highest within 20 cm of the odor port, and decreases thereafter (**Supplementary Fig. 6f**).These

results together suggest that the choice-selective ensembles reflecting decision making during

the odor-cue period transiently encode the choice during the initial track period, but the decision

is subsequently maintained by a distinct ensemble during the working-memory period

associated with the spatial delay on the central arm.

DISCUSSION

Our results provide new insight into the mechanisms of rhythmic coordination of

hippocampal–prefrontal ensembles by beta rhythms for odor-cued associations and decision

making. We found that during an odor-place associative memory task, beta rhythms govern

physiological coordination between the olfactory bulb, hippocampus, and PFC. During the odor

sampling and decision-making period, task-responsive single unit and ensemble activity in the

CA1-PFC network discriminates between choices and can reliably predict upcoming behavior.

Further, CA1-PFC ensemble dynamics and beta coherence during this period are linked to

latency of decisions. Despite this link, we did not find evidence for direct beta phase modulation

of choice-encoding putative pyramidal neurons. Instead, we found that interneurons in CA1

were strongly locally and cross-regionally phase modulated by beta. This suggests that

coordination by beta rhythms may sculpt network activity through interneuron modulation,

enabling emergence of task-related ensemble dynamics in local circuits to support decision

making. Our results thus suggest that beta oscillations play a key modulatory role in enabling

temporal evolution of ensemble dynamics in the CA1-PFC network for odor-cued decision

making, delineating a novel mechanism through which rhythmic coordination supports cognition.

The mechanisms underlying encoding and recall of associations between sensory cues in

the environment, and subsequent use of these associations to guide decisions, are of

fundamental interest. Sensory cue-elicited recall and decision making during goal-directed

behavior involves widespread networks encompassing sensory regions, medial temporal

memory regions, and prefrontal executive function regions. Prominent odor-driven oscillations

have been described in these areas[5,47-53,80], which can potentially coordinate these long-range

networks to enable utilization of familiar olfactory cues to guide behavior. Here, the use of an

odor-cued T-maze task allowed us to examine which rhythms enable coordination of olfactory-

hippocampal-prefrontal networks, and whether these rhythms play a role in patterning ensemble

activity in hippocampal-prefrontal network to enable memory-guided decision making.

In this task, the time period between odor onset and odor port disengagement provided a

temporal window corresponding to odor-cued recall and priming of the subsequent decision to

turn toward the reward location. We found increases in power and coherence of both beta (~15-

30 Hz) and RR (~7-8 Hz) across the olfactory-hippocampal-prefrontal network during this odor

sampling and decision-making period. However, only the strength of beta coherence, and not

RR coherence, between the hippocampus and PFC was correlated with shorter decision

latency. Further, while CA1-PFC RR coherence remained unchanged between odor-cued trials

and trials where only air was presented, high beta coherence was specific to odor-cued trials

corresponding to a decision-making task and was lower on air-cued trials corresponding to

random choices. Based on these findings, we speculate that encountering a familiar odor

stimulus and efficiently utilizing this associative memory for a decision, rather than respiration or

movement preparation[81], elicits the engagement of the hippocampal-prefrontal network by the

beta rhythm.

Interestingly, although hippocampal SWRs have been linked to internal recall and

planning[72,73,82], there was very low prevalence of hippocampal SWRs during odor sampling,

suggesting SWRs are not directly involved in odor-cued associative memory and decision

making while the animal is re-encountering the familiar cue. Instead, our results indicate that

beta plays a key role in mediating this process, in addition to coordinating entorhinal-

hippocampal networks for odor-cued recall, as described previously[5]. In our experiments, rats

were very familiar with the task and odor-place associations, with high performance levels.

Therefore, the lack of SWRs during the decision-making period could reflect that these

memories had been previously consolidated into neocortex during learning, resulting in a shift

from largely hippocampal-dependent processing[5] to processing that is more reliant on

hippocampal-cortical dialogue via the beta rhythm.

Odor-driven gamma rhythms at 40-100 Hz have also been reported in odor-memory

tasks[47,66,83], and may play a complementary role with beta oscillations. It has been hypothesized

that local olfactory networks may be governed by gamma rhythms for odor processing early in

stimulus sampling, before shifting to a beta-dominant network state as downstream regions are

engaged[47,84]. Our results corroborate this hypothesis by reinforcing the role of the beta rhythm in

long-range coordination with a wider network outside the olfactory system for cognitive

processing of odor stimuli. We speculate that sensory modality-specific rhythms may play a

general role in cue-driven mnemonic decision making by coordinating sensory and cognitive

areas, which can be tested in future studies.

Our analysis of single units in the hippocampus and prefrontal cortex revealed a group of

cells that were selectively responsive in the odor task period, similar to previous reports in the

hippocampus[5,85,86]. However, we found that these selective cells often exhibited "opposite"

selectivity on incorrect trials compared to correct trials, indicating that these cells do not respond

solely to the perceptual qualities of the odor, in which case the response would be similar on all

presentations of a particular odor regardless of the trial outcome. Instead, this response

suggests coding of the behavioral choice associated with the odor cue, resembling findings from

studies of combined cue modalities and cue-context associations[1,6-8,10,86-88]. Thus, the CA1-PFC

neural response during odor sampling corresponds to the decision in response to the odor-place

association. Future studies that combine recording from other olfactory regions, such as piriform

cortex, together with hippocampus and PFC can potentially unveil how the cue representation

evolves from odor perception to the recall-based decision.

Task-responsive neural populations exhibited differential activity patterns in response to the

two odor-associations during decision making, and the animal's upcoming choice could be

predicted from this ensemble activity. Correlation between the timing of ensemble odor

discrimination and choice execution indicates that the emergence of the neuronal representation

coincides with and potentially primes the cognitive decision. This emergence of neural

ensembles that reflect associative memories governing decision making may also be indicative

of a physiological mechanism for dynamic reactivation of memory engrams upon re-

encountering the familiar odor stimuli[89,90]. We also found evidence that beta rhythms may

govern the temporal evolution of CA1-PFC neural ensemble dynamics leading to memory-

guided decision making, as demonstrated by the small but significant correlations between the

strength of beta coherence, the timing of ensemble discrimination, and the behavioral decision

latency. It remains unclear, however, how these neural dynamics and their relationship to the

beta rhythm evolve as animals learn new associations. One possibility is that they resemble the

dynamics observed in the hippocampal-entorhinal circuit, in which coordination of the network at

the beta rhythm and choice-selective neural activity emerge gradually as animals learn the

task[5].

Similarly, CA1-OB beta coherence is strong during odor memory tasks and is known to

increase over the course of learning[58]. Although CA1-OB beta coherence was high during odor

sampling in our task, we observed no significant relationship between CA1-OB coherence and

task performance. Since previous reports suggest that this coherence is linked to the learning

process, it is possible that a more direct relationship between coherence strength and

performance would be observed only during learning, but not in this case where the odor

association and task are familiar. Choice-coding ensemble dynamics may evolve in parallel with

the increase in CA1-OB beta coherence over learning, similar to what has been reported in the

hippocampal-entorhinal circuit[5]. This possibility can be investigated by examining network

dynamics and ensemble activity across multiple olfactory and cognitive areas during novel odor-

place learning or reversal learning.

It is also noteworthy that we observed different mechanisms underlying odor-cued decision

making versus subsequent maintenance of the representation of the choice during a spatial

delay period. Odor-driven beta coherence leads to emergence of ensemble selectivity during

the decision-making period, which is predictive of the animal's upcoming choice, but these

ensembles maintain their choice-selectivity only transiently after the decision execution as

animals embark on the spatial trajectory toward reward. This selective coding is not maintained

by the same ensembles during running, but instead other spatially modulated cells in CA1 and

PFC maintain choice coding on the track, including the spatial delay period (common central

arm on the T-maze) activity. Thus, beta-driven ensembles mediate memory-guided decision

making in the hippocampal-prefrontal network, but choice selective activity is then subsequently

maintained by theta-driven spatially modulated activity, similar to reports in spatial working

memory tasks[77].

The temporal evolution of ensemble activity underlying odor-cued decision making, and

its relationship to beta oscillations, is reminiscent of temporal coding of odor stimuli mediated by

oscillations in the olfactory system[50,52]. Previous findings indicate that spike timing modulation

according to the phase of prominent network rhythms can organize task-encoding neural

ensembles to support memory guided behavior and decision-making[42,86,91-94]. Interestingly

however, we found that although the strength of local beta and RR phase-modulation was linked

to correct decisions, putative pyramidal neurons that encoded the choice were no more likely to

be phase-locked than chance level. Notably, phase locking was stronger and more prevalent for

RR compared to the beta rhythm, even though behavioral decision latency and choice-coding in

the underlying ensembles was more linked to beta coherence in the network. Further, we found

evidence that slightly different populations of cells are modulated by the two ongoing rhythms

during decision making, implying that beta and RR represent two simultaneous modes of

rhythmic coordination in the network[49]. This joint modulation of the underlying cell populations,

along with our finding of strong cross-frequency coupling between the two rhythms, leads us to

the interpretation that beta and RR coordinate the network cooperatively during odor-cued

decision making, rather than acting as independent but parallel processes. Previous reports of

RR in olfactory processing[51,52,55], along with evidence that multiple rhythms can simultaneously

modulate ongoing processes[49,95,96], suggests that RR is the dominant modulator coordinating

the sensory element of the task, while beta coordination is key for employing the sensory cued

association to make a decision. This interpretation is further supported by our results from un-

cued air sessions, which did not involve memory-guided behavior, in which we found a

reduction in beta coherence in the network but no change in RR coherence. This suggests that

the sensory component of this process is maintained as the animal continues sniffing even in

the absence of an explicit cue, whereas beta coordination is only engaged when a familiar cue

is utilized for a decision.

In contrast to pyramidal cells, we found that a large population of CA1 interneurons were

strongly modulated by the beta rhythm locally and cross-regionally and the strength of this

modulation was linked to task performance. This suggests that the beta rhythm can function by

modulating CA1 interneuron activity, which sculpts ensemble dynamics in the local circuits

governing decision making. In this manner, beta oscillations may play a role in establishing

communication and organization of activity in sensory and cognitive networks enabling

decisions based on cued associations. Thus, oscillatory phase-modulation may be indicative of

a general network state that enables coordination.

METHODS

All experimental procedures were approved by the Brandeis University Institutional

Animal Care and Usage Committee (IACUC) and conformed to US National Institutes of Health

guidelines. Eight male Long-Evans rats (3-6 months, 450-650 g) were used for experiments.

Animals were housed individually in a dedicated climate-controlled animal facility on a 12-hour

light/dark cycle. All experiments were carried out during light cycle. Upon arrival, animals were

provided ad libitum access to food and water and handled regularly to habituate them to human

contact.

Behavior Apparatus

An olfactometer (MedAssociates Inc.) was used for dispensing odors. The olfactometer

continuously dispensed clean air to the odor port until receiving a signal to open a solenoid

valve which caused air to flow through liquid odorants, resulting in odorized air dispensed to the

odor port. A vacuum tube attached to the odor port was used to continuously collect any

residual odorized air between trials. Infrared beams were used at the odor port and reward wells

to determine the precise timing of entry and exit from these areas.

Odor-Place Association Task Training

Once rats reached a minimum threshold weight of 450 g, they were food restricted to no

less than 85% of their free-feeding baseline weight. For initial behavioral training, rats were

familiarized with the behavior room, the sleep box, running on a raised track to receive

evaporated milk reward, and sniffing odors presented in the odor port. Following this

habituation, rats were trained to hold their nose in the odor port for a minimum of 500 ms, with

an auditory tone indicating when this 500-ms time threshold was reached. However, the rats

could continue to sniff the odor for any longer duration of time, and odor would be continuously

dispensed until they disengaged from the odor port. Throughout all training and experiments, if

the rat exited the odor port before this threshold was reached, no reward was dispensed

regardless of the rat's choice and the rat was required to re-initiate the trial. These prematurely

terminated trials were excluded from all analyses. For each trial, the odor sampling period was

defined as the time from the onset when rat's nose broke the infrared beam to offset when the

beam break was terminated, and odor stimulus was stopped.

Animals were subsequently trained on the olfactory association. On each trial, one of

two possible odors was dispensed at the odor port in a pseudo-random order. Odor 1 (Heptanol

– pine/citrus scent) indicated that the rat should go to Reward 1 to receive reward. Odor 2 (ethyl

butyrate – strawberry scent) indicated that the rat should choose Reward 2 (**Fig. 1a**). If the rat

ultimately made the correct choice, evaporated milk reward would be dispensed at the chosen

reward port upon triggering the infrared beam, whereas upon an incorrect choice no reward was

dispensed.

Associative memory training was shaped in steps. The rats first learned the association

between the odors and "right" vs "left" reward locations with reward wells close to the odor port.

On subsequent training days, the reward wells were moved further and further away from the

odor port, until rats could comfortably perform the task on the full T-maze (81 cm long center

stem, and 43cm long reward arms). Two rats were not trained to run on the full T-maze, and

instead were just required to perform the association with the reward wells within easy reach on

either side of the odor port. For one animal, the maze had a shortened stem (40 cm instead of

81 cm), but the reward wells were still at the ends of the T arms. Task performance was

calculated as the proportion of correct trials. Rats were trained until they could perform the task

with at least 80% accuracy for 3 consecutive days.

Once training was complete, animals were once again provided with *ad libitum* access to

food until they reached at least 600 g, before undergoing surgery. After surgery but before

recording, rats were briefly re-trained on the association until they could again perform the task

with at least 80% accuracy. On recording days, animals were allowed to continue performing

the task until they reached satiation, about 100-150 trials per day. Task epochs were interleaved

by sleep epochs, in which rats spent about 20 minutes in an opaque sleep box, with a sleep

epoch as the first and last epoch of each day.

Un-Cued Air Sessions

Four of the animals were tested on one session each in which only clean air was

dispensed at the odor port, instead of two distinct odors. Reward was available at a randomly

chosen reward port on each trial; although, since the trials were un-cued, the animals would

often randomly choose the "incorrect" side and no reward was dispensed (**Supplementary**

Figure 3f). All other aspects of the task were the same as the odor-cued task.

Surgical Procedures

Surgical implantation techniques were performed as described previously[31,98]. Animals

were implanted with a microdrive array containing 30 independently moveable tetrodes targeting

right dorsal hippocampal region CA1 (-3.6 mm AP and +2.2 mm ML, 10-12 tetrodes), right PFC

(+3.0 mm AP and +0.7 mm ML10-13 tetrodes), and right olfactory bulb (+7.2 mm AP and +0.8

mm ML, 1-4 tetrodes). Post-operative analgesic care was provided for 48 hours after surgery to

minimize pain and discomfort. In two of the eight animals used for experiments, a nasal

thermocouple was implanted in addition to the microdrive array to record the respiratory rhythm.

The thermocouple was placed in the left nostril though a hole drilled in the skull at +7.5 mm

anterior to the cribriform suture. The thermocouple wire was secured using dental acrylic and

soldered to the same printed circuit board as the tetrodes.

Tetrode Recordings

For 1-2 weeks following surgery, tetrodes were gradually lowered to the desired depths.

Hippocampal tetrodes were targeted to the pyramidal layer of CA1 using characteristic EEG

patterns (sharp wave polarity, theta modulation) and neural firing patterns as previously

described[78,97]. The final placement of tetrodes was confirmed in histological preparations using

Nissl staining post-mortem. One tetrode in corpus callosum served as hippocampal reference,

and another tetrode in overlying cortical regions with no spiking signal served as PFC reference.

A ground screw (GND) installed in the skull overlying cerebellum also served as a reference,

and LFP was recorded relative to this GND. All spiking activity was recorded relative to the local

reference tetrode. Only LFP activity was recorded from olfactory bulb. Electrodes were not

moved at least 4 hours before and during the recording day to reduce drift, and were micro-

adjusted at the end of each recording day to sample new cell populations.

Data were collected using a SpikeGadgets data acquisition system and software

(SpikeGadgets LLC). Spike data were sampled at 30 kHz and bandpass filtered between 600

Hz and 6 kHz. LFP signals were sampled at 1.5 kHz and bandpass filtered between 0.5 Hz and

400 Hz. The animal's position and running speed were recorded with an overhead color CCD

camera (30 fps) and tracked by color LEDs affixed to the headstage.

Data Analysis and Statistics

All data analysis was performed in MATLAB using custom code unless otherwise noted.

Error bars indicate standard deviation unless otherwise noted. Significance was defined using

an alpha of 0.05. Statistical details including tests used, p-values, and n values can be found in

figure legends, and are described in-depth below.

Local Field Potential

Trial-averaged spectrograms and coherograms were calculated using multi-taper

spectral methods included in the Chronux package for MATLAB (www.chronux.org). To get the

beta filtered local field potential (LFP) signal, raw LFP (with respect to GND) was band pass

filtered at 15-30 Hz using a zero-phase IIR filter. Amplitude, phase, and envelope magnitude of

the signals were obtained using a Hilbert transform. Beta power and coherence were z-scored

to the epoch mean. Similarly, the respiratory rhythm signal was obtained by band pass filtering

the raw LFP at 7-8 Hz. Due to the overlap between the RR and the theta rhythm (6-12 Hz), to

get an accurate measure of RR power and coherence without leakage from the theta rhythm,

this signal was z-scored to time-matched periods during immobility while the animal was

consuming reward.

Bootstrap Tests

Bootstrap tests for **Supplementary Fig. 3g** were performed when coherence on odor-

cued and air-cued trials were compared, to account for the much larger percentage of odor-

cued trials. Data points on odor trials were randomly downsampled with replacement to match

the number of air trials, and the mean was calculated for this new set of datapoints. This

downsampling was done 1000 times, to create a new, bootstrapped distribution of means. The

observed mean value for the air trial distribution was compared to the bootstrapped distribution.

P-values were calculated by counting the number of values the bootstrapped distribution that

were greater than or equal to the observed mean value, and dividing by the total number of re-

samples (1000). P-values less than 0.05 were considered statistically significant, and thus

rejected the null hypothesis that the two observed distributions had equal means.

The bootstrap test for **Fig. 4c** was performed similarly, except that the CA1 and PFC cell

ensembles were resampled to create new ensembles of 50 cells each. The timing of PV

divergence for each resampled ensemble was calculated as described below (see **Population**

Differential Index methods). This procedure was repeated for 500 iterations to generate the

distributions shown in **Fig. 4c**.

Sharp-Wave Ripple Detection

Hippocampal sharp-wave ripples were detected as previously described[31,78,98]. Briefly,

the locally referenced LFP signal from CA1 tetrodes was filtered in the ripple band (150-250

Hz), and the envelope of the ripple-filtered LFPs was determined using a Hilbert transform.

SWR events were detected as contiguous periods when the envelope stayed above 3 SD of the

mean on at least one tetrode for at least 15 ms.

Cross-frequency Coupling

Phase-amplitude coupling between RR and beta was computed for **Supplementary Fig.**

2g as previously described[99]. In brief, the phases of RR were divided into 20 degree bins, and

the mean amplitude of the beta rhythm at each phase was calculated. The mean amplitudes

were then normalized by dividing each bin by the sum of amplitudes across all bins. The

strength of phase-amplitude coupling was determined by comparing the amplitude distribution to

a uniform distribution by calculating the modulation index (MI), which is based on the Kullback–

Leibler (KL) distance but normalized so that values fall between 0 and 1, where a value of 0

indicates a uniform distribution of beta amplitudes across RR phases. Significance was

determined by comparing the calculated MI to a null distribution generated by shuffling the trial

number assignments of the RR phase series; this maintains the structure of the underlying

rhythm but randomly aligns the beta amplitudes on each trial to each trial sequence RR phases.

Single Unit Analysis

Spike sorting was done semi-automatically using MountainSort[100,101], with manual

curation. Only well-isolated units were used for analysis. Putative interneurons and pyramidal

cells were classified based on average firing rate and spike width, as described previously[31,98].

Units were classified as interneurons if they had an average firing rate exceeding 7 Hz and an

average spike width under 0.3 ms. All other units were considered putative pyramidal cells.

Units were excluded from analysis if they had fewer than 100 spikes across all sessions. A

small number of pyramidal cells only had spikes during sleep epochs, and these were excluded

from analysis[78,102] since all analysis done here focused exclusively on the task periods.

Task Responsiveness

Task responsiveness was calculated as a change in firing rate following odor onset,

compared to a pre-stimulus period of the same length of time as the odor sampling period on

each trial leading up to odor port engagement. Sampling events were only considered if the

animal held its nose in the odor port for longer than 0.50 seconds and proceeded to a reward

port. Statistical significance was determined from the Wilcoxon signed rank test of those trial-

matched rate differences for each odor identity separately. If a cell showed a significant change

up or down from baseline for at least one of the odors, it was considered task responsive. Of

note, there was only a single unit analyzed whose firing rate changed in opposite directions from

baseline for the two odors, the remainder showed the same direction of change in firing rate for

the two odors.

Choice Selectivity

795   Firing rates during odor sampling were calculated as the number of spikes as a function of

796   time from odor-port engagement to odor-port disengagement. Choice selectivity was calculated

797   using the following equation:

$$SI = \frac{\lambda_1 - \lambda_2}{\lambda_1 + \lambda_2}$$

799   Where λ_1 is the firing rate vector for Odor 1 trials, and λ_2 is firing rate vector for Odor 2 trials.

800   *SI* = 1 indicates that the cell only responded on Odor 1 trials, whereas *SI* = -1 indicates that the

801   cell only responded on Odor 2 trials. To determine significance, a null distribution was

802   generated in which the odor identities were shuffled across trials. Cells were considered choice-

803   selective if the SI fell outside of 1.5 s.d. from the mean of the null distribution.

Population Differential Index

The population differential index (PDI) was calculated as described in Igarashi et al.,

2014. For this analysis, all task-responsive cells were pooled across animals and days into a

single population. Mean firing rates were calculated in 100 ms bins from 0 to 1 second aligned

to odor onset to obtain population vectors for each of the two odors. At each time bin, the

correlation coefficient (CC) was calculated between the Odor 1 response vector and Odor 2

response vector. This CC was subtracted from 1 to obtain the PDI:

812
$$1 - CC = PDI$$

such that PDI = 1 indicates that the population responses for the two odors are completely

distinct, whereas PDI = 0 indicates that the responses are identical. Chance-level PDI was

computed by shuffling the odor identities across trials and creating a null distribution. The real

PDI was then compared to the null distribution across the odor sampling time window. The

timepoint at which the population responses considered significantly distinct from each other

was defined as the first timepoint at which the real PDI surpassed the 95% confidence interval

of the null distribution.

Individual Trial PDI

A similar PDI analysis was employed to examine population dynamics on a trial-by-trial

basis, in which the PDI was computed for single trials individually. Cells were not pooled across

animals, and only sessions with at least 3 task-responsive cells were considered for analysis.

The PDI was computed by calculating the CC between the trial PV and the average PV of all

trials of the opposite odor in that session.

GLM

A generalized liner model (GLM) with a log link function was constructed to predict

reward choice based on neural activity during the odor sampling period. Activity from all task-

responsive neurons that were active on at least 10 trials was included. Neural population activity

from different length time bins from 0.1 seconds to 1 second aligned to odor onset was used for

prediction, i.e. 0-0.1s, 0-0.2s … 0-1.0s. Five-fold cross validation was used to test prediction.

For each fold, the session's trials were randomly partitioned into five equally sized sets. Four of

the five sets were used to train the GLM model and the remaining set was used to test. The

prediction accuracy was calculated by dividing the number of correctly predicted trials by the

total number of trials used for testing for each fold.

Significance was determined by performing the same procedure as described above but

shuffling the trial outcomes to obtain a null distribution. At each time bin used for the prediction,

a rank-sum test was performed on the prediction accuracy using the real data compared to the

shuffled data.

Phase Locking

For all phase-locking analyses, the tetrode in each region with the most cells on

each given day was used to measure oscillatory phase of either beta or RR. Phase

locking of individual cells to the beta and respiratory rhythms was calculated by pooling

the spike phases of each cell during the odor-sampling periods and performing a

Rayleigh Z test for circular non-uniformity. For each cell, the mean direction of the von

Mises distribution of spike-phases was used as the preferred phase.

Occupancy Maps

For all spatial field analyses, only the 5 animals that were trained on the full T-maze

were used; the three animals trained on the truncated maze were excluded due to insufficient

spatial data. Two-dimensional occupancy maps were generated by calculating occupancy in 2-

cm square spatial bins from epochs in which the animals running speed exceeded 3 cm/sec and

convolving with a 2d Gaussian (σ= 2 pixels).

Place Field Determination

2-D occupancy-normalized firing rate maps were generated by dividing the spikes at

each 2-D pixel by the unsmoothed occupancy at that pixel, and then and smoothing with a

Gaussian kernel of (σ = 2 pixels, or 4 cm).

Linearized trajectory occupancy maps were calculated as previously described[31,97,98]. Briefly,

the rats 2d spatial coordinates were first segmented into run epochs based on contiguous bouts

of time in which the animals running speed exceeded 3 cm/sec. Then, the position of the animal

during each 'run epoch' was categorized by its origin and destination, and each position was

assigned to one of 100 (1.23 cm) bins from the origin to the destination of that route. Then the

total number of spikes at each bin was divided by that bin's occupancy, and the map was

convolved by a Gaussian kernel with a standard deviation of 2 pixels (2.5 cm).

Place field peak was calculated as the peak rate bin on the smoothed, linearized rate map,

and place fields were only considered for trajectories in which the cell had a peak firing rate of at

least 1 Hz. Place field width was calculated using a flood fill-algorithm in which the edges were

defined as the closest bins to the peak bin in which the rate fell below 25% of the peak rate.

Place field sparsity and information scores were calculated as previously described[103]. A cell

was determined to have a place field if its peak firing rate along that trajectory was ≥ 2 S.D.

above the mean of a bootstrapped distribution generated by circularly shifting the spikes in time

for each individual run, and if the field covered less than 75% of the linearized trajectory. When

analyzing the place field characteristics of choice-selective cells (**Fig. 6**, **Supplementary Fig.**

6), the field of each outbound journey was analyzed separately so as to prevent 'choosing'

certain fields over others.

Trajectory Selectivity

Trajectory selective cells were identified using a previously validated method[31]. Briefly,

the linearized spatial tuning curve was calculated separately for each outbound trajectory and

the correlation between those trajectories was computed. A cell was identified as trajectory

selective if this correlation value exceeded the 95th percentile of a distribution wherein each

outbound trajectory identity was shuffled and the correlation recalculated.

To measure trajectory selectivity as it related to decision period selectivity, we used an

analogous method to the odor selectivity index. Briefly we calculated the mean firing rate along

each run beginning one half second following odor port exit and once the animals speed

exceeded 3 cm/sec to the end of that run (when the animal either reached the goal or its

velocity fell below 3 cm/sec for more than ½ second). The difference in these mean firing rates

across runs was divided by the sum of those two mean rates to generate a trajectory selectivity

index.

Bayesian Decoder

Choice identity decoding was performed as previously described[102]. Briefly, a

memoryless Bayesian decoder was built for each of the two choice identities from spikes

occurring in the odor sampling period. Then, the likelihood of each choice (x) was reconstructed

from their posterior probabilities given the spikes occurring at each segment along the maze on

each run (p(x | spikes) = p(spikes | x) * p(x) / p(spikes)). Run activity was defined as contiguous

bouts following the odor sampling period when the animal was traveling above 3 cm/sec.

Additionally, to prevent overlap between odor-period spiking and run spiking, the run periods

were defined beginning 0.5 seconds following odor port disengagement time. We assumed that

the N active cells fired independently and followed a Poisson process, giving the following

equation.

907
$$P(X|spikes) = C * (\prod_{i=1}^{N} f_i(X)^{spikes_i}) * e^{-\tau} \sum_{i=1}^{N} f(X)$$

Where C is a normalization constant across the two choice identities. The p-value was

calculated from the Gaussian statistics of a Monte Carlo random shuffle (200 shuffles) of choice

identity during the odor sampling period. When choice identity decoding was calculated from the

likelihoods of activity from each run, the decoding was performed in the same 5-fold leave-one-

out fashion as was used in the GLM analyses, and the p value was calculated from the same

Monte Carlo random shuffle of the training set route identities as the odor period based

decoding.

Data Availability

The behavioral and electrophysiological data supporting the findings in this study are archived

on servers at Brandeis University and are available upon request to the corresponding author.

Code Availability

All data processing, analyses and statistics in this study were conducted using open-source

package Mountainsort (https://github.com/flatironinstitute/mountainsort) and custom code in

MATLAB (R2018), unless otherwise noted. All custom code is available upon request to the

corresponding author.

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AUTHOR CONTRIBUTIONS

S.P.J. conceived and designed the study, C.A.S. performed experiments and analyzed the data,

J.B. analyzed the data, E.K. contributed to experiments, S.P.J. and C.A.S. wrote the manuscript

with input from all authors.

COMPETING INTERESTS STATEMENT

The authors declare no competing interests.

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 Figure 1: Odor–place associative memory and decision-making task

a. Schematic of the odor-cued T-maze task. Odors 1 (heptanol) and 2 (ethyl butyrate) were

delivered at the odor port in pseudo-random order. Presentation of Odors 1 and 2 was

associated with milk reward at Reward locations 1 and 2, respectively. Animals had to recall

odor-space associations on each trial and utilize the association to choose the correct

reward location.

b. Performance of each animal (n = 8) on the odor-cued T-maze task (animals 1 - 5) or

truncated odor-cued task (animals 6 - 8; truncated task, without spatial delay period) across

multiple sessions (grey dots). Animal average is indicated by black bars. Dashed line

indicates chance level.

c. Odor sampling duration across all sessions (n = 38) on correct and incorrect trials (signed-

rank test, p = 0.71).

d. Turn direction away from odor port in relation to chosen reward well. Pie charts indicate the

fraction of trials in which, at the odor port, animals turned in the same direction versus the

opposite direction as the reward well that they would ultimately choose. Sessions in which

animals ran the truncated task without spatial delay period were excluded. (correct trials: n =

1624 same direction, 32 opposite direction, binomial test, p = 0; incorrect trials: n = 499

same direction, 21 opposite direction, p = 1.4e-108).

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Figure 2: Beta rhythms support decision making based on odor-place associations

a. Examples of thermocouple and LFP traces from one tetrode in each region during presentation of odor from one trial, aligned to odor port disengagement. Area between dashed lines indicates odor sampling period. Top to bottom: Respiratory rhythm recorded via thermocouple, CA1 signal, beta band (15-30 Hz) filtered CA1 signal, PFC signal, beta band filtered PFC signal, OB signal, beta band filtered OB signal.

b. Time-frequency plot showing power spectra aligned to odor offset. Color scale represents z-scored power. Area between dashed lines indicates average odor sampling period. Beta band is marked by blue bracket (15-30 Hz). RR band is marked by pink bracket (7-8 Hz). Thermocouple signal (TC), n = 12 sessions, max 0.69, min -0.31; CA1: n = 38 sessions, max 0.26, min -0.35; PFC: n = 38 sessions, max 0.60, min -0.16; and OB: n = 38 sessions, max 2.17, min -0.24.

c. Top: CA1-PFC coherence spectra for one animal during the full task time window from odor sampling (area between white dashed lines, aligned to odor offset) to average reward onset time (solid line) (n = 4 sessions, max 0.84; min -0.41). Bottom: CA1-PFC coherence aligned to odor offset across all animals (n = 38 sessions, max 0.51; min -0.34). Color scale represents z-scored power.

d. Beta (top) and RR (bottom) CA1-PFC coherence during odor periods and time-matched pre-odor periods. (signed-rank tests, n = 38 sessions. Beta coherence: p = 6.7e-6***; RR coherence: p = 0.36).

e. Beta (top) and RR (bottom) CA1-PFC coherence as a function of decision latency on correct trials. (n = 38 sessions, beta coherence: r = -0.54, p = 4.4e-4***; RR coherence: r = 0.03, p = 0.87).

f. CA1-PFC beta coherence during 500 ms window preceding odor port exit, and 500 ms window preceding reward well exit (signed rank test, n = 38 sessions, p = 1.2e-7***).

g. Beta (top) and RR (bottom) CA1-PFC coherence on correct and incorrect trials. (Signed-

rank tests, n = 38 sessions. Beta coherence: p = 0.38; RR coherence: p = 0.81).

h. Beta (top row) and respiratory rhythm (RR) (bottom row) power on correct and incorrect

trials in CA1 and PFC. (Signed-rank tests. n = 38 sessions. Beta power: CA1: p = 0.08;

PFC: p = 8.3e-4***. RR power: CA1: p = 0.26; PFC: p = 0.16.)

i. Maps of T-maze showing the spatial distribution of z-scored CA1 beta power (left. max

1.49; min -0.19), PFC beta power (middle-left, max 1.63; min -0.18), CA1-PFC beta

coherence (middle-right, max 1.16; min -0.19), and SWR rate (right, max 1.34; min 0).

Plots are for a single session from one animal.

j. Number of SWR events per trial during odor sampling and reward consumption on

correct trials (signed-rank test, n = 38 sessions, p =1.1e-7***).

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Figure 3: Single neurons in CA1 and PFC exhibit choice-selectivity during decision-

making period

a. Sankey diagram showing the number of CA1 cells that were classified into different

categories. Sizes of partitions are proportional to raw numbers.

b. Example PSTH and raster plot for a single choice-selective CA1 neuron on correct trials,

aligned to odor-port disengagement. Shaded areas indicate s.e.m. Firing rates are shown in

Hz, referring to spikes/second.

c. PSTH and raster plot for the same neuron in (b), but only for incorrect trials.

d. Selectivity index (SI) of all choice-selective cells in CA1 on correct trials (left) and incorrect

trials (right), aligned to odor-port disengagement. SI is calculated as the difference in firing

rate between Odor 1 trials and Odor 2 trials, divided by the sum of these firing rates. SI is

color coded, where blue indicates an SI of 1 (absolute Choice 1 preference), red indicates

an SI of -1 (absolute Choice 2 preference) and grey indicates an SI of 0 (not selective). Cells

are sorted according to peak selectivity on correct trials and sorting order is the same for

both plots.

e. Correlation between correct trial SI and incorrect trial SI for all choice-selective CA1 cells (n

= 42, r = -0.42, p = 0.003**).

f-j.   Same as a-e, but for PFC cells. Correlation in j: n = 49, r = -0.53, p = 1.8e-5***.

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 Figure 4: Neural ensemble responses during decision making are governed by beta

coordination and predict the upcoming choice

a. Normalized firing rate of all task-responsive cells in CA1 (top) and PFC (bottom) during a 1

second window before odor port disengagement.

b. Discriminability between population vectors (PVs) on Odor 1 versus Odor 2 presentations,

for CA1 task-responsive population (top, n = 125 cells) and PFC task-responsive

population (bottom, n = 157 cells), across time bins aligned to odor port disengagement.

Dissimilarity between PVs is scaled and shown as a PV differential index (PDI), where 0

indicates identical responses. Colored line indicates real data, grey shaded area indicates

95% confidence intervals of shuffled distribution.

c. PV divergence time in CA1 and PFC. Divergence time is quantified as the first time point

where the real data PDI surpasses the mean + 2 s.d. of the shuffled PDI distribution.

Bootstrap test, n = 50 samples with replacement, 500 iterations. Boxplots indicate

interquartile ranges of bootstrapped distributions. CA1: median = 0.19 seconds prior to

odor-port disengagement, interquartile range = 0.06; PFC: median = 0.23 seconds prior to

odor-port disengagement, interquartile range = 0.06; (bootstrap test; p = 0.31)

d. Timing of peak PV discriminability (PDI) on each trial aligned to odor onset as a function of

decision latency for CA1 (top) and PFC (bottom). Decision latencies were divided into six

equally sized subgroups (sextiles) for visualization, but correlation coefficients were

calculated using trials. Error bars show s.e.m. at each sextile (CA1: n = 2071 trials, r =

0.16, p = 1.1e-12***; PFC: n = 2081 trials, r = r = 0.06, p = 0.007**). Individual trial rasters

in Supplementary Figure 4j.

e. Timing of peak PV discriminability (PDI) on each trial as a function of beta coherence. Beta

coherence distribution was divided into six equally sized subgroups (sextiles) for

visualization, but correlation coefficients were calculated using trials. Error bars show

s.e.m. at each sextile (CA1: r = -0.12, p = 2.1e-8***; PFC: r = -0.04, p = 0.09).

f.   Prediction of animal's choice of reward well by a GLM according to ensemble activity

during odor sampling across varying length time windows aligned to decision time. Colored

error bars indicate real data mean ± s.d., whereas grey error bars indicate shuffled data

mean ± s.d. Cells used for prediction include all task-responsive putative pyramidal cells in

CA1 (left) and PFC (right). Stars indicate prediction time windows where the fraction of

correctly predicted trials was significantly higher than the fraction from the shuffled data

(rank-sum tests, * = p < 0.05).

g.   As in (i) but including both putative pyramidal and interneurons in ensembles for GLM

prediction.

h.   Histograms showing distributions of peak timings of cross-correlations between CA1 and

PFC cell pairs. Peaks falling above zero indicate CA1 leading, whereas peaks falling below

zero indicate PFC leading. One-sample Wilcoxson signed rank tests (H_0: μ = 0 ms). Top-

left: CA1-PFC pyramidal pairs, n = 603 pairs, p = 0.07; top-right: CA1 interneuron-PFC

pyramidal pairs, n = 462 pairs, p = 6.0e-4***; bottom-left: CA1 pyramidal-PFC interneuron

pairs, n = 130 pairs, p = 0.14, bottom right: CA1-PFC interneuron pairs, n = 85 pairs, p =

0.33.

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a

% of spikes

-2π   0   2π
Beta Phase

% of spikes

-2π   0   2π
Beta Phase

b

π/2

π   0

3π/2

CA1
PFC

c Beta (Pyramidal Cells)

*   **   n.s.   n.s.

Rayleigh Z score

7
5

CA1-CA1   PFC-PFC   CA1-PFC   PFC-CA1

● Correct   ○ Incorrect

d RR (Pyramidal Cells)

*   n.s.   n.s.   n.s.

Rayleigh Z score

CA1-CA1   PFC-PFC   CA1-PFC   PFC-CA1

● Correct   ○ Incorrect

e

% of Pyramidal Cells

***   ***

CA1   PFC

■ Beta   ■ RR

f

% of Pyramidal Cells

n.s.   n.s.

CA1   PFC

■ Choice Selective
□ Beta Phase Locked
▨ Both
■ Chance

g

CA1-CA1
π/2

π   0

3π/2

CA1-PFC
π/2

π   0

3π/2

h Beta (Interneurons)

***   ***

Rayleigh Z score

CA1-CA1   CA1-PFC

● Correct   ○ Incorrect

i

% of Interneurons

n.s.   n.s.

CA1   PFC

■ Choice Selective
□ Beta Phase Locked
▨ Both
■ Chance

Figure 5: CA1 and PFC cells phase lock to beta and respiratory rhythms during decision

making

a. Example spike-phase histograms from two example cells that are phase locked to the beta

rhythm. Top: CA1 cell (Rayleigh Z test, n = 242 spikes, z = 15.5, p = 1.5e-7); bottom: PFC

cell (n = 99 spikes, z = 4.86, p = 0.007). Phase axes are duplicated for visibility.

b. Polar histogram of preferred beta phases for all task-responsive CA1 (n = 125 cells,

Rayleigh Z test, z = 7.9, p = 3.4e-4) and PFC (n = 157 cells, z = 5.0, p = 0.006) cells. Arrows

indicate mean phase direction and magnitude.

c. Rayleigh Z scores of spike-phases for all task-responsive pyramidal cells phase-locked to

the beta rhythm locally and cross-regionally on correct versus incorrect trials. (signed-rank

tests, CA1 cells phase locked to CA1 beta: n = 28 cells, p = 0.03*; PFC-PFC: n = 8 cells, p =

0.008**, CA1-PFC: n = 18 cells, p = 0.40; PFC-CA1: n = 12 cells, p = 0.20).

d. As in (c), but for spike-phases for all pyramidal cells phase-locked to local RR. (signed-rank

tests, CA1-CA1: n = 103 cells, p = 0.04*; PFC-PFC: n = 21 cells, p = 0.24; CA1-PFC: n = 85

cells, p = 0.27; PFC-CA1: n = 49 cells, p = 0.30).

e. Percentage of cells in CA1 and PFC that were phase locked to either beta or RR (z-tests for

proportions; CA1: n = 37 cells phase-locked to beta, n = 112 cell phase-locked to RR, z = -

9.8, p = 3.2e-20; PFC: n = 17 cells phase-locked to beta, n = 60 cells phase-locked to RR, z

= -5.5, p = 1.8e-8).

f. Percentage of cells that are choice-selective (solid bars), phase-locked to the beta rhythm

(outlined bars), and both choice-selective and phase-locked (striped bars). Grey bars

indicate chance level of cells being both choice-selective and phase-locked, error bars

indicate the range of cell percentages that fall within the 95% bounds of the chance binomial

distribution. (binomial test, CA1: p = 0.08; PFC: p = 0.16).

g.   Polar histogram of preferred beta phases for all task-responsive CA1 interneurons phase-

locked to the local CA1 beta rhythm (top, n = 44 cells, z = 8.0, p = 2.9e-4***) and CA1

interneurons phase-locked to the PFC beta rhythm (bottom, n = 25 cells, z = 22.5, p = 1.8e-

11***) Arrows indicate mean phase direction and magnitude.

h.   Rayleigh Z scores of spike-phases for all task-responsive CA1 interneurons phase-locked

locally and cross-regionally to the beta rhythm on correct versus incorrect trials. (signed-rank

tests, CA1-CA1: n = 44 cells, p = 8.2e-9***; CA1-PFC: n = 25 cells, p = 1.2e-5***).

i.   As in (f), but for interneurons. (binomial test; CA1: p = 0.11; PFC: p = 0.20)

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Figure 6: Representations of choice and space are maintained independently during

delay period

a. Example choice-selective units (CA1, first two columns, PFC, last two columns) with spatial

   fields on the track. Top row: Heat map illustrating spatial fields during run bouts. Middle row:

   Linearized spatial tuning curves for outbound left and right run trajectories. Bottom row:

   PSTHs showing odor responses during decision-making period (Odor selectivity indices, left

   to right: 0.92, -0.43, -0.40, -0.57).

b. Spatial field prevalence in task-unresponsive and task-responsive cells in CA1 (left) and

   PFC (right). CA1: 273/477 (57%) of task-unresponsive cells, and 71/108 (66%) of task-

   responsive cells had spatial fields (binomial test: $p = 0.03^*$); PFC: 76/160 (48%) of task-

   unresponsive cells, and 83/128 (66%) of task-responsive cells had spatial fields (binomial

   test: $p = 2.7e-5^{***}$).

c. Correlation between firing rates during run and firing rates during odor sampling period for

   all putative pyramidal cells in CA1 (left) and PFC (right). (CA1: n = 585 cells, r = 0.39, p =

   3.0e-37; PFC: n = 288 cells, r = 0.68, p = 1.2e-62).

d. Spatial field width for odor unresponsive and odor responsive units in CA1 (left) and PFC

   (right). If a unit had a spatial field on both outbound trajectories, each field was counted

   separately. (Rank-sum tests; CA1: n = 452 fields, p = 0.15; PFC: n = 207 fields, p = 0.92).

e. Trajectory selectivity scores of choice-selective units according to preferred choice (Rank

   sum tests, CA1: p = 0.26; PFC: p = 0.20).

f. Decoding of choice identity by naïve Bayesian classifier according to CA1 (left) and PFC

   (right) task-responsive ensemble activity at five equally sized spatial quintiles along the full

   run trajectory of the maze. 1 spatial quintile = 24.6 cm (123 cm / 5). Colored error bars

   indicate real data mean ± s.d. whereas grey error bars indicate shuffled data mean ± s.d.

1359   Stars indicate quintiles where the fraction of correctly decoded trials was significantly higher

1360   than the fraction from the shuffled data (rank-sum tests, * = $p < 0.05$).

1361 g. As in (f), but decoding of choice identity according to CA1 (left) and PFC (right) spatially-

1362   modulated ensemble activity at each spatial quintile. (rank-sum tests, * = $p < 0.05$, ** = $p <$

1363   0.01).