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Neural correlates of individual odor preference in *Drosophila*

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Abstract

Behavior varies even among genetically identical animals raised in the same environment. However, little is known about the circuit or anatomical origins of this individuality. We show individual *Drosophila* odor preferences (odor-vs-air and odor-vs-odor) are predicted by idiosyncratic calcium dynamics in olfactory receptor neurons (ORNs) and projection neurons (PNs), respectively. Variation in ORN presynaptic density also predicts odor-vs-odor preference. The ORN-PN synapse appears to be a locus of individuality where microscale variation gives rise to idiosyncratic behavior. Finally, simulating microscale stochasticity in ORN-PN synapses of a 3,062 neuron model of the antennal lobe recapitulates patterns of variation in PN calcium responses matching experiments. Our results demonstrate how physiological and microscale structural circuit variations can give rise to individual behavior, even when genetics and environment are held constant.

Keywords: individuality, neural circuits, sensory processing, olfaction, behavioral preference, variation, *Drosophila*, antennal lobe, calcium imaging, expansion imaging

Introduction

Individuality is a fundamental aspect of behavior that is observed even among genetically-identical animals reared in similar environments. We are specifically interested in individuality that is evident as idiosyncratic differences in behavior that persist for much of an animal's lifespan. Such variability is observed across species including round worms (Stern et al., 2017), aphids (Schuett et al., 2011), fish (Laskowski et al., 2022), mice (Freund et al., 2013), and people (Johnson et al., 2010). Small, genetically tractable model species, such as *Drosophila*, are particularly promising for discovering the genetic and neural circuit basis of individual behavior variation. Flies exhibit individuality in many behaviors (Werkhoven et al., 2021), and the mechanistic origins of this variation has been studied for phototactic preference (Kain et al., 2012), temperature preference (Kain et al., 2015), locomotor handedness (Ayroles et al., 2015; Buchanan et al., 2015; de Bivort et al., 2022), object-fixated walking (Linneweber et al., 2020), and odor preference (Honegger et al., 2019). Generally, the neural substrates of individuality are poorly understood, though in a small number of instances nanoscale circuit correlates of individual behavioral biases have been identified (Linneweber et al., 2020; Skutt-Kakaria et al., 2019). We hypothesize that as sensory cues are encoded and transformed to produce motor outputs, their representation in the nervous system becomes increasingly idiosyncratic and predictive of individual behavioral responses. We seek to identify "loci of individuality" – sites at which this idiosyncrasy emerges.

Olfaction in the fruit fly *Drosophila melanogaster* is an amenable sensory system for identifying loci of individuality, as 1) individual odor preferences can be recorded readily, 2) neural representations of odors can be measured via calcium imaging, 3) the circuit elements of the pathway are well-established, and 4) a deep genetic toolkit enables mechanism-probing experiments. The neuroanatomy of the olfactory system, from the antenna through its first central-brain processing neuropil, the antennal lobe (AL), is broadly stereotyped across individuals (Couto et al., 2005; Grabe et al., 2015; Wilson et al., 2004). The AL features ~50 anatomically identifiable microcircuits called glomeruli (Figure 1A). Each glomerulus represents an odor-coding channel and receives axon inputs from olfactory receptor neurons (ORNs) expressing the same olfactory receptor gene (de Bruyne et al., 2001). Uniglomerular projection neurons (PNs) carry odor information from each glomerulus deeper into the brain (Jeanne and Wilson, 2015). AL-intrinsic local neurons (LNs) project among glomeruli (Chou et al., 2010) and modulate odor representations (Wilson and Laurent, 2005). Glomerular organization is a key stereotype of the AL; using glomeruli as landmarks, one can identify comparable ORN axons and PNs across individuals.

Several possible determinants of individual odor preference can already be hypothesized for the fly olfactory circuit (Rihani and Sachse, 2022). Individual flies differ in their PN calcium responses to identical odor stimuli, as well as their odor-vs-odor preference choices (Honegger et al., 2019). The extent of preference variability depends on dopamine and serotonergic

modulation (Honegger et al., 2019). Neuromodulation clearly plays a role in the regulation of behavioral individuality (Maloney, 2021), but its effects vary by modulator and behavior (de Bivort et al., 2022; Kain et al., 2012). With respect to wiring variation, the number of ORNs and PNs innervating a given glomerulus varies within hemispheres (Tobin et al., 2017) and across individuals (Grabe et al., 2016; Schlegel et al., 2020), as does the glomerulus-innervation pattern of individual LNs (Chou et al., 2010). Subpopulations of LNs and PNs express variable serotonin receptors (Sizemore and Dacks, 2016), so the effects of neuromodulation and wiring may interact to influence individuality. Little is known about possible molecular or nanoscale correlates of individual behavioral bias. Thus, individual odor preference could have its origins in many potential mechanisms, ranging from circuit wiring to modulation to neuronal intrinsic properties.

Outside the olfactory system, there are two instances in which microscale circuit variation is known to predict individual behavioral preference. Wiring asymmetry in an individual fly's dorsal cluster neurons is predictive of the straightness of its object-oriented walking behavior (Linneweber et al., 2020), and left-right asymmetry in the density of presynaptic sites of protocerebral bridge - lateral accessory lobe-projecting neurons predicts an individual fly's idiosyncratic turning bias (Skutt-Kakaria et al., 2019).

In this work, we sought to identify loci of individuality by measuring odor preferences and neural responses to odors in the same individuals and asking whether the latter predicted the former. We found that idiosyncratic calcium responses in specific neurons were predictive of olfactory preferences – variation in ORN responses predicts odor-vs-air preference; variation in PN responses predicts odor-vs-odor preference. Zooming into a molecular component, variation in the scaffolding protein Bruchpilot in ORN presynaptic terminals is also predictive of odor preference variation. To unify these results and connect wiring variation to circuit outputs, we simulated developmental variation in a 3,062-neuron spiking model of the antennal lobe. Simulated stochasticity in the ORN-PN synapse recapitulated our empirical findings. Thus, we identified the ORN-PN synapse as a locus of individuality in fly odor preference, demonstrating that behaviorally-relevant variation in neural circuits can be found in the sensory periphery at the nanoscale.

Results

Individual flies encode odors idiosyncratically

Focusing on behavioral variation within a genotype, we used isogenic animals expressing the fluorescent calcium reporter GCamp6m (Chen et al., 2013) in either of the two most peripheral neural subpopulations of the *Drosophila* olfactory circuit, ORNs or PNs (Figure 1E). We performed head-fixed 2-photon calcium imaging after measuring odor preference in an untethered assay (Honegger et al., 2019) (Figure 1B-D, Figure 1 – figure supplement 1A).

Individual odor preferences are stable over timescales longer than this experiment (Figure 1 – figure supplement 1B-E).

We measured volumetric calcium responses in the antennal lobe (AL), where ORNs synapse onto PNs in ~50 discrete microcircuits called glomeruli (Figure 1A) (Couto et al., 2005; Grabe et al., 2015). Flies were stimulated with a panel of 12 odors plus air (Figure 1D, Figure 1 – figure supplement 2) and *k*-means clustering was used to automatically segment the voxels of 5 glomeruli from the resulting 4-D calcium image stacks (Figure 1E, Figure 1 – figure supplement 4, Materials and Methods) (Couto et al., 2005). Both ORN and PN odor responses were roughly stereotyped across individuals (Figure 1G,H), but also idiosyncratic (Honegger et al., 2019). Responses in PNs appeared to be more idiosyncratic than ORNs (Figure 1J); a logistic linear classifier decoding fly identity from glomerular responses was more accurate when trained on PN than ORN responses (Figure 1 – figure supplement 5A). While the responses of single ORNs are known to vary more than those of single PNs (Wilson, 2013), our recordings represent the total response of all ORNs or PNs in a glomerulus. This might explain our observation that ORNs exhibited less idiosyncrasy than PNs. PN responses were more variable within flies, as measured across the left and right hemisphere ALs, compared to ORN responses (Figure 1 – figure supplement 5C), consistent with the hypothesis that odor representations become more idiosyncratic farther from the sensory periphery.

Individual ORN responses predict odor-air preference

Next we analyzed the relationship of idiosyncratic coding to odor preference, by asking in which neurons (if any) did calcium responses predict individual preferences of flies choosing between air and an aversive odor (3-octanol, OCT; Figure 1 – figure supplement 1B; Supplementary Video 1). Because we could potentially predict preference (a single value) using numerous glomerular-odor predictors, and had a limited number of observations (dozens), we used dimensional reduction to make parsimonious predictions. We computed the principal components (PCs) of the glomerulus-odor responses (in either ORNs or PNs) across individuals (Figure 1G-I; Figure 1 – figure supplement 3, Figure 1 – figure supplement 7) and fit linear models to predict the behavior of individual flies from their values on the odor response PCs. PC 1 of ORN activity was a significant predictor of odor preference ($r = 0.48$; $p = 0.0099$; Figure 1K,L). PC 1 of PN activity was also correlated with odor preference in separate model training and testing experiments (Figure 2 – figure supplement 1; statistics from combined train and test data: $r = 0.29$, $p = 0.035$, Figure 1K,M). Our interpretation is that ORN responses are idiosyncratic and predict individual odor-vs-air preference, and that these idiosyncrasies are transmitted to PNs, where they remain predictive of behavioral responses.

How should we interpret the calcium PCs only predicting odor preference with $r = \sim0.4$? This value falls short of 1.0 due to at least two factors: 1) any non-linearity in the relationship between calcium responses and behavior, and 2) sampling error in, and temporal instability of, behavior

and calcium responses over the duration of the experiment. A lower bound on the latter can be estimated from the repeatability of behavioral measures over time (Figure 1 – figure supplement 1B-E). To disentangle these effects, we performed a statistical analysis that estimated model performance in the absence of sampling error and drift in the measurement of behavior and calcium responses, i.e., the strength of the linear relationship between latent behavior and calcium states (Figure 4 – figure supplement 1; Materials and Methods). This analysis implies the nominal correlation of 0.48 between behavior and PC1 of ORN calcium responses corresponds to a correlation between latent calcium and behavior states (ρ_{signal}) of 0.64. This makes intuitive sense because the raw model R^2 (0.23) is close to the behavior repeatability R^2 (0.27), an upper-limit on model performance (Figure 1 – figure supplement 1B). The model predicting odor-vs-air behavior from PC1 of PN calcium responses has an estimated ρ_{signal} of 0.40 (Figure 4).

PN, but not ORN, responses predict odor-odor preference

Variation in the sensory periphery has been previously implicated as a driver of behavioral variation (Michelson et al., 2017; Osborne et al., 2005), but we wondered whether ORNs would be a locus of individuality for a behavior requiring the comparison of two odors (rather than just the sensation of a single odor). So we next determined if idiosyncratic calcium responses could predict individual preferences in an odor-vs-odor choice (Figure 1 – figure supplement 1D,E; (Honegger et al., 2019); Supplementary Video 2), specifically between the aversive monomolecular odorants (OCT) and 4-methylcyclohexanol (MCH). We assessed if any of the first 5 PCs of PN calcium responses was a linear predictor of individual odor-vs-odor preferences. PC 2 accounted for 15% of preference variance in a training set of 47 flies (Figure 2 – figure supplement 1C). This PC 2-based model explained 31% of preference variance on test data (n=22 flies) (Figure 2 – figure supplement 1D). Combined train/test statistics ($r = 0.45$; $p = 0.0001$) are presented in Figure 1N,P. We estimate that the correlation between between latent PN calcium and odor-vs-odor behavioral states is $\rho_{signal} = 0.75$ (Figure 4).

No PCs of ORN neural activity could linearly predict odor preference beyond the level of shuffled controls (n=35 flies) (Figure 1N,O; Figure 4). The best ORN PC model only predicted odor-vs-odor behavior with a nominal R^2 of 0.031 ($\rho_{signal} = 0.30$). Projecting ORN data onto PC 2 of PN responses (the successful model) did not predict odor-vs-odor behavior (R^2=0.060). Therefore, whereas idiosyncratic ORN responses (and PN responses) were predictive of odor-vs-air preferences, only PN responses were predictive of odor-vs-odor preferences.

We next sought an intuitive understanding of the models linking calcium responses and odor preference. The loadings of the ORN and PN PCs indicate that variation across individuals was correlated at the level of glomeruli much more strongly than odorant (Figure 1 – figure supplements 3, 7). This suggests that stochastic variation in the olfactory circuit results in individual-level fluctuations in the responses of glomeruli-specific rather than odor-specific

responses. In the case of the odor-vs-air model, the PC 1 loadings of both ORN and PN neural activity were non-negative across all glomerulus-odor response dimensions (Figure 2A,D), apparently representing each individual's total response in all glomerulus-odorant combinations. Indeed, a linear model that simply sums all calcium responses in ORNs (Figure 2B,E) predicted behavior with R^2=0.25 (ρ_{signal} = 0.67); for PN responses, it was somewhat predictive, though less so (R^2=0.098; ρ_{signal} = 0.43). For both ORNs and PNs, the model's slope parameter (β) was negative (Table 1), meaning that stronger AL responses correlated with stronger preference for air, consistent with OCT being aversive. Thus, flies whose ORNs and PNs respond, as a population, more strongly to OCT are more likely to avoid it.

In the odor-vs-odor preference model, the loadings of PC2 of PN calcium responses contrast the responses of the DM2 and DC2 glomeruli with opposing weights (Figure 2G), suggesting that the activation of DM2 relative to DC2 predicts the likelihood of a fly preferring OCT to MCH. Indeed, a linear model constructed from the total DM2 minus total DC2 PN response (Figure 2H) predicted individual preference for OCT versus MCH (R^2=0.12; ρ_{signal} = 0.59; Figure 2I). The model beta coefficient was negative (Table 1), indicating that greater activation of DM2 vs DC2 correlates with preference for MCH. With respect to odor-vs-odor behavior, we conclude that the relative responses of DM2 vs DC2 in PNs largely explains an individual's preference.

Odor experience has been shown to modulate subsequent AL responses (Golovin and Broadie, 2016; Iyengar et al., 2010; Sachse et al., 2007). This raises the possibility that our models were actually predicting individual flies' past odor experiences (i.e., the specific pattern of odor stimulation flies received in the behavioral assay) rather than their preferences. To address this, we imposed the specific odor experiences of previously tracked untethered flies (in the odor-vs-odor assay) on naive "yoked" control flies (Figure 2J) and measured PN odor responses of the yoked flies. Applying the PN PC 2 model to the yoked calcium responses did not predict flies' odor experience (R^2=0.019; Figure 2K). Thus, the responses of DM2 vs DC2 in PNs do not predict individual open-loop odor experiences.

Previous work found that PN response transients, rather than fixed points, contain more odor identity information (Mazor and Laurent, 2005). We therefore asked at which times during odor presentation an individual's neural responses could best predict odor preference. Applying each of our three successful calcium-to-behavior models (ORN PC1-odor-vs-air, PN PC1-odor-vs-air, PN PC2-odor-vs-odor) to the time-varying calcium signals, we found that in all cases, behavior prediction generally rose during odor delivery (Figure 4 – figure supplement 2A-C). In ORNs, the predictive accuracy remained high after odor offset, whereas in PNs it declined. Thus, the overall sensitivity of ORNs that appears to predict odor-vs-air preferences may persist after odor stimulation ends. The times during which calcium responses predicted individual behavior generally aligned to the times during which a linear classifier could decode odor identity from

ORN or PN responses (Figure 4 – figure supplement 2D), suggesting that idiosyncrasies in odor encoding predict individual preferences.

Variation in a presynaptic scaffolding protein predicts odor-odor preference variation

We next investigated how structural variation in the nervous system might underlie the variations in neural activity that correlate with idiosyncratic behavior. Because PN, but not ORN, calcium responses predicted odor-vs-odor preference, we hypothesized that a circuit element between ORNs to PNs could confer onto PNs behaviorally-relevant physiological idiosyncrasies absent in ORNs. We therefore imaged presynaptic T-bar density in ORNs using transgenic mStrawberry-tagged Brp-Short, immunohistochemistry and confocal microscopy (Mosca and Luo, 2014) after measuring individual preference for OCT versus MCH (Figure 3A). Brp-Short density was quantified as fluorescence intensity / glomerulus volume for 4 of the 5 focus glomeruli (Figure 3B, Figure 3 – figure supplement 1A-F; DL5 was not readily segmentable across samples, but was dispensable in all behavior-predicting models). This measure was consistent across hemispheres (Figure 3 – figure supplement 1C), while also showing variation among individuals.

To begin assessing the relationship between presynaptic structural variation and behavior, we calculated the principal components of Brp-Short density across individuals. PCs 1 and 2 were qualitatively similar to those in our calcium imaging experiments: PC 1 was non-negative positive across glomeruli, reflecting global average staining intensity, and PC 2 exhibited a sign contrast between DC2 loadings and all other glomerulus loadings (Figure 3 – figure supplement 1G). As in the PN calcium response models, PC 2 of Brp-Short density was the best predictor of odor-vs-odor preferences in training data (Figure 3D-E, Figure 3 – figure supplement 1I, R^2 = 0.22, n=22 flies) and for test data (Figure 3 – figure supplement 1J, R^2 = 0.078, n=31 flies; statistics from combined train and test data: R^2 = 0.088, n=53 flies, Figure 3F). We tested our intuitive hypothesis that PC 2 captures the differential response of DM2 vs DC2 by applying the "DM2 minus DC2 model" (Figure 2H) to the Brp-Short data (Figure 3G). While this rudimentary model did not attain statistical significance, it had a negative beta coefficient, implying that higher presynaptic density in DM2 compared to DC2 correlates with preference for MCH (Table 1), consistent with the beta parameter of the PN calcium response model.

The range of differences between DM2 and DC2 Brp-Short staining across individuals (-50% to 40%; normalized by the average of the two glomeruli) was less than that of PN calcium response differences (-60% to 100%; Figure 3 – figure supplement 2), suggesting that presynaptic density variation is not the full explanation of calcium response variability. Consistently, the best presynaptic density models are less predictive of behavior than the best calcium response models (R^2=0.088 vs R^2=0.22; ρ_{signal} = 0.51 and 0.75, respectively; Figure 2 – figure supplement 1C,D vs Figure 3 – figure supplement 1I,J). Nevertheless, differences in presynaptic inputs to DM2 and DC2 PNs may contribute to variation in DM2 and DC2 calcium dynamics, in turn giving rise to individual preferences for OCT versus MCH.

To help formulate hypotheses about what variable Brp-Short staining represented on a microstructural level, we performed paired behavior and expansion microscopy (Asano et al., 2018; Gao et al., 2019) in flies expressing Brp-Short specifically in DC2-projecting ORNs (Supplementary Video 3). Expansion yielded a ~4-fold increase in linear resolution, allowing imaging of individual Brp-Short puncta (Figure 3 – figure supplement 1K) (Gao et al., 2019). While the sample size (n=8) of this imaging pipeline did not warrant a formal modeling analysis, the trend between density of Brp-Short in DC2 and odor-vs-odor preference was more consistent with a positive correlation than the trend between Brp-Short volume and odor-vs-odor preference (Figure 3 – figure supplement L,M). These results hint that variation in the density of Bruchpilot protein within presynaptic sites, rather than other biophysical properties, may be a critical factor underlying physiological and behavioral individuality.

Developmental stochasticity in a simulated AL recapitulates empirical PN response variation

Finally, we sought an integrative understanding of how synaptic variation plays out across the olfactory circuit to produce behaviorally-relevant physiological variation. We developed a leaky-integrate-and-fire model of the entire AL, comprising 3,062 spiking neurons and synaptic connectivity taken directly from the *Drosophila* hemibrain connectome (Scheffer et al., 2020). After tuning the model to perform canonical AL computations, we introduced different kinds of stochastic variations to the circuit and determined which (if any) would produce the patterns of idiosyncratic PN response variation observed in our calcium imaging experiments (Figure 5A). This approach assesses potential mechanisms linking developmental variation in synapses to physiological variation that apparently drives behavioral individuality.

The biophysical properties of neurons in our model (Figure 5B, Table 2) were determined by published electrophysiological studies (See *Voltage model* in Materials and Methods) and were similar to those used in previous fly models (Kakaria and de Bivort, 2017; Pisokas et al., 2020). The polarity of neurons was determined largely by their cell type (ORNs are excitatory, PNs predominantly excitatory, and LNs predominantly inhibitory – explained further in Materials and Methods). The strength of synaptic connections between any pair of AL neurons was given by the hemibrain connectome (Scheffer et al., 2020) (Figure 5C). Odor inputs were simulated by injecting current into ORNs to produce spikes in those neurons at rates that match published ORN-odor recordings (Münch and Galizia, 2016), and the output of the system was recorded as the firing rates of PNs during odor stimulation (Figure 5D). At this point, there remained only four free parameters in our model, the relative sensitivity (postsynaptic current per upstream action potential) of each AL cell type (ORNs, PNs, excitatory LNs and inhibitory LNs). We explored this parameter space manually, and identified a configuration in which AL simulation (Figure 5 – figure supplement 1) recapitulated four canonical properties seen experimentally (Figure 5 – figure supplement 2): 1) typical firing rates at baseline and during odor stimulation (Bhandawat et al., 2007; Dubin and Harris, 1997; Jeanne and Wilson, 2015; Seki et al., 2010), 2)

a more uniform distribution of PN firing rates compared to ORN rates (Bhandawat et al., 2007), 3) greater separation of PN odor representations compared to ORN representations (Bhandawat et al., 2007), and 4) a sub-linear transfer function between ORNs and PNs (Bhandawat et al., 2007). Thus, our simulated AL appeared to perform the fundamental computations of real ALs, providing a baseline for assessing the effects of idiosyncratic variation.

We simulated stochastic individuality in the AL circuit in two ways (Figure 5E): 1) glomerular-level variation in PN input-synapse density (reflecting a statistical relationship observed between glomerular volume and synapse density in the hemibrain, Figure 5 – figure supplement 4), and 2) bootstrapping of neuronal compositions within cell types (reflecting variety in developmental program outcomes for ORNs, PNs, etc.). Supplementary Video 4 shows the diverse connectivity matrices attained under these resampling approaches. We simulated odor responses in thousands of ALs made idiosyncratic by these sources of variation, and in each, recorded the firing rates of PNs when stimulated by the 12 odors from our experimental panel (Figure 5F, Figure 5 – figure supplement 1).

To determine which sources of variation produced patterns of PN coding variation consistent with our empirical measurements, we compared principal components of PN responses from real idiosyncratic flies to those of simulated idiosyncratic ALs. Empirical PN responses are strongly correlated at the level of glomeruli (Figure 5G; Figure 1 – figure supplement 7). As a positive control that the model can recapitulate this empirical structure, resampling PN input-synapse density across glomeruli produced PN response correlations strongly organized by glomerulus (Figure 5I). As a negative control, variation in PN responses due solely to poisson timing of ORN input spikes (i.e., absent any circuit idiosyncrasy) was not organized at the glomerular level (Figure 5H). Strikingly, bootstrapping ORN membership yielded a strong glomerular organization in PN responses (Figure 5J). The loadings of the top PCs under ORN bootstrapping are dominated by responses of a single glomerulus to all odors, including DM2 and DC2. This is reminiscent of PC2 of PN calcium responses, with prominent (opposite sign) loadings for DM2 and DC2. Bootstrapping LNs, in contrast, produced much less glomerular organization (Figure 5K), with little resemblance to the loadings of the empirical calcium PCs. The PCA loadings for simulated PN responses under all combinations of cell type bootstrapping and PN input-synapse density resampling are given in Figure 5 – figure supplement 5.

DM2 and DC2 (also DL5) stand out in the PCA loadings under PN input-synapse density resampling and ORN bootstrapping (Figure 5I,J), suggesting that behaviorally-relevant PN coding variation is recapitulated in this modeling framework. To formalize this analysis, for each idiosyncratic AL, we computed a “behavioral preference” by applying the PN PC2 linear model (Figure 1N,P) to simulated PN responses. We then determined how accurately a linear classifier could distinguish OCT- vs MCH-preferring ALs in the space of the first 3 PCs of PN responses (Figure 5 – figure supplement 6). High accuracy was attained under PN input-synapse density

resampling and ORN bootstrapping (sources of circuit variation that produced PN response loadings highlighting DM2 and DC2). Thus, developmental variability in ORN populations may drive patterns of PN physiological variation that in turn drive individuality in odor-vs-odor choice behavior.

Discussion

We found elements of the *Drosophila* olfactory circuit where patterns of physiological activity emerge that are predictive of individual behavioral preferences. These circuit elements can be considered loci of individuality, as they appear to harbor the origins of idiosyncratic preferences among isogenic animals reared in the same environment. Specifically, the total responsiveness of ORNs predicts idiosyncratic odor-vs-air preferences, and contrasting glomerular activation in PNs predicts idiosyncratic odor-vs-odor preferences (Figures 1, 2). Both of these circuit elements are in the olfactory sensory periphery, suggesting that behavioral idiosyncrasy arises early in the sensorimotor transformation. We were particularly surprised at the extent to which PN activity could predict preference between two aversive odors. We estimated that the strength of the correlation between latent PN activity and behavioral states was 0.75 (Figure 4B).

Previous work has found mammalian peripheral circuit areas are predictive of individual behavior (Britten et al., 1996; Michelson et al., 2017; Newsome et al., 1989; Osborne et al., 2005), but this study is among the first (Linneweber et al., 2020; Mellert et al., 2016; Skutt-Kakaria et al., 2019) to link cellular-level circuit variants and individual behavior in the absence of genetic variation. Another key conclusion is that loci of individuality are likely to vary, even within the sensory periphery, with the specific behavioral paradigm (i.e., odor-vs-odor or odor-vs-air). Our ability to predict behavioral preferences was limited by the repeatability of the behavior itself (Figure 4 – figure supplement 1). Low persistence of odor preference may be attributable to factors like internal states or plasticity. It may be fruitful in future studies to map circuit elements whose activity predicts trial-to-trial behavioral fluctuations within individuals.

Seeking insight into the molecular basis of behaviorally-relevant physiological variation, we imaged Brp in the axon terminals of the ORN-PN synapse, using confocal and expansion microscopy. Brp glomerular (and probably puncta) density was a predictor of individual odor-vs-odor preferences (Figure 3). Higher Brp in DM2 predicted stronger MCH preference, like higher calcium responses in DM2 PNs, suggesting that variation in PN inputs underlies PN physiological variation. This is consistent with the recent finding of a linear relationship between synaptic density and excitatory postsynaptic potentials (Liu et al., 2022) and another study in which idiosyncratic synaptic density in central complex output neurons predicts individual locomotor behavior (Skutt-Kakaria et al., 2019). The predictive relationship between Brp and behavior was weaker than that of PN calcium responses, suggesting there are other determinants,

such as other synaptic proteins, neurite morphology, or the influence of idiosyncratic LNs (Chou et al., 2010) modulating the ORN-PN transformation (Nagel et al., 2015).

To integrate our synaptic and physiological results, we implemented a spiking model with 3,062 neurons and synaptic weights drawn directly from the fly connectome (Scheffer et al., 2020) (Figure 5). With light parameter tuning, this model recapitulated canonical AL computations, providing a baseline for assessing the effects of idiosyncratic stochastic variation. The apparent variation in odor responses across simulated individuals (Figure 5F) is less than that seen in the empirical calcium responses (Figure 1H), likely due to 1) biological phenomena missing from the model, 2) the lack of measurement noise, and 3) the fact that our perturbations are applied to the connectome of a single fly. When examining PCA loadings, however, simulating idiosyncratic ALs by varying PN input synapse density or bootstrapping ORNs produced correlated PN responses across odors in DC2 and DM2, matching our experimental results. These sources of variation specifically implicate the ORN-PN synapse (like our Brp results) as an important substrate for establishing behaviorally-relevant patterns of PN response variation.

The flies used in our experiments were isogenic and reared in standardized laboratory conditions that produce reduced behavioral individuality compared to enriched environments (Akhund-Zade et al., 2019; Körholz et al., 2018; Zocher et al., 2020). Yet, even these conditions yield substantial behavioral individuality. We do not expect variability in the expression of the flies' transgenes to be a major driver of this individuality, as wildtype flies have a similarly broad distribution of odor preferences (Honegger et al., 2019). The ultimate source of stochasticity in this behavior remains a mystery, with possibilities ranging from thermal fluctuations at the molecular scale to macroscopic, but seemingly irrelevant, variations like the exact fill level of the culture media (Honegger and de Bivort, 2018). Developing nervous systems employ various compensation mechanisms to dampen out the effects of these fluctuations (Marder, 2011; Tobin et al., 2017). Behavioral variation may be beneficial, supporting a bet-hedging strategy (Hopper, 1999) to counter environmental fluctuations (Akhund-Zade et al., 2020; Honegger et al., 2019; Kain et al., 2015; Krams et al., 2021). Empirically, the net effect of dampening and accreted ontological (Gomez-Marin and Ghazanfar, 2019) fluctuations is individuals with diverse behaviors. This process unfolds across all levels of biological regulation. Just as PN response variation appears to be partially rooted in glomerular Brp variation, the latter has its own molecular roots, including, perhaps, stochasticity in gene expression (Li et al., 2017; Raj et al., 2010), itself a predictor of idiosyncratic behavioral biases (Werkhoven et al., 2021). Improved methods to longitudinally assay the fine-scale molecular and anatomical makeup of behaving organisms throughout development and adulthood will be invaluable to further illuminate the mechanistic origins of individuality.

Materials and Methods

Data and code availability

All raw data, totaling 600 GB, are available via hard drive from the authors. A smaller (7 GB) repository with partially processed data files and MATLAB/Python scripts sufficient to generate figures and results is available at Zenodo (doi:10.5281/zenodo.8092972).

Fly rearing

Experimental flies were reared in a *Drosophila* incubator (Percival Scientific DR-36VL) at 22° C, 40% relative humidity, and 12:12h light:dark cycle. Flies were fed cornmeal/dextrose medium, as previously described (Honegger et al., 2019). Mated female flies aged 3 days post-eclosion were used for behavioral persistence experiments. Mated female flies aged 7 to 15 days post-eclosion were used for all paired behavior-calcium imaging and immunohistochemistry experiments.

Fly stocks

The following stocks were obtained from the Bloomington *Drosophila* Stock Center: P{20XUAS-IVS-GCaMP6m}attP40 (BDSC #42748), w[*]; P{w[+mC]=Or13a-GAL4.F}40.1 (BDSC #9945), w[*]; P{w[+mC]=Or19a-GAL4.F}61.1 (BDSC #9947), w[*]; P{w[+mC]=Or22a-GAL4.7.717}14.2 (BDSC #9951), w[*]; P{w[+mC]=Orco-GAL4.W}11.17; TM2/TM6B, Tb[1] (BDSC #26818). Transgenic lines were outcrossed to the isogenic line isokh11 (Honegger et al., 2019) for at least 5 generations prior to being used in any experiments. GH146-Gal4 was a gift provided by Y. Zhong (Honegger et al., 2019). w; UAS-Brp-Short-mStrawberry; UAS-mCD8-GFP; + was a gift of Timothy Mosca and was not outcrossed to the isokh11 background (Mosca and Luo, 2014).

Odor delivery

Odor delivery during behavioral tracking and neural activity imaging was controlled with isolation valve solenoids (NResearch Inc.) (Honegger et al., 2019). Saturated headspace from 40 ml vials containing 5 ml pure odorant were serially diluted via carbon-filtered air to generate a variably (10-25%) saturated airstream controlled by digital flow controllers (Alicat Scientific) and presented to flies at total flow rates of ~100 mL/min. The odor panel used for imaging was comprised of the following odorants: 2-heptanone (CAS #110-43-0, Millipore Sigma), 1-pentanol (CAS #71-41-0, Millipore Sigma), 3-octanol (CAS #589-98-0, Millipore Sigma), hexyl-acetate (CAS #142-92-7, Millipore Sigma), 4-methylcyclohexanol (CAS #589-91-3, Millipore Sigma), pentyl acetate (CAS #628-63-7, Millipore Sigma), 1-butanol (CAS #71-36-3, Millipore Sigma), ethyl lactate (CAS #97-64-3, Millipore Sigma), geranyl acetate (CAS #105-87-3, Millipore Sigma), 1-hexanol (CAS #111-27-34, Millipore Sigma), citronella java essential oil (191112, Aura Cacia), and 200 proof ethanol (V1001, Decon Labs).

Odor preference behavior

Odor preference was measured at 25°C and 20% relative humidity. As previously described (Honegger et al., 2019), individual flies confined to custom-fabricated tunnels were illuminated with infrared light and behavior was recorded with a digital camera (Basler) and zoom lens (Pentax). The odor choice tunnels were 50 mm long, 5 mm wide, and 1.3 mm tall. Custom real-time tracking software written in MATLAB was used to track centroid, velocity, and principal body axis angle throughout the behavioral experiment, as previously described (Honegger et al., 2019). After a 3-minute acclimation period, odorants were delivered to either end of the tunnel array for 3 minutes. Odor preference score was calculated as the fraction of time spent in the reference side of the tunnel during odor-on period minus the time spent in the reference side of the tunnel during the pre-odor acclimation period.

Behavioral preference persistence measurements

After measuring odor preference, flies were stored in individual housing fly plates (modified 96-well plates; FlySorter, LLC) on standard food, temperature, humidity, and lighting conditions. Odor preference of the same individuals was measured 3 and/or 24 hours later. In some cases, fly tunnel position was randomized between measurements. We observed that randomization had little effect on preference persistence.

Calcium imaging

Flies expressing GCaMP6m in defined neural subpopulations were imaged using a custom-built two-photon microscope and ultrafast Ti:Sapphire laser (Spectra-Physics Mai Tai) tuned to 930 nm, at a power of 20 mW out of the objective (Olympus XLUMPlanFL N 20x/1.00 W). For paired behavior and imaging experiments, the time elapsed between behavior measurement and imaging ranged from 15 minutes to 3 hours. Flies were anesthetized on ice and immobilized in an aluminum sheet with a female-fly-sized hole cut in it. The head cuticle between the antennae and ocelli was removed along with the tracheae to expose the ALs from the dorsal side. Volume scanning was performed using a piezoelectric objective mount (Physik Instrumente). ScanImage 2013 software (Vidrio Technologies) was used to coordinate galvanometer laser scanning and image acquisition. Custom Matlab (Mathworks) scripts were used to coordinate image acquisition and control odor delivery. 256 by 192 (x-y) pixel 16-bit tiff images were recorded. The piezo travel distance was adjusted between 70 and 90 μm so as to cover most of the AL. The number of z-sections in a given odor panel delivery varied between 7 and 12 yielding a volume acquisition rate of 0.833 Hz. Odor delivery occurred from 6-9.6s of each recording.

Each fly experienced up to four deliveries of the odor panel. The antennal lobe being recorded (left or right) was alternated after each successful completion of an odor panel. Odors were delivered in randomized order. In cases where baseline fluorescence was very weak or no obvious odor responses were visible, not all four panels were delivered.

514 ***Glomerulus segmentation and labeling***
515 Glomerular segmentation masks were extracted from raw image stacks using a *k*-means
516 clustering algorithm based on time-varying voxel fluorescence intensities, as previously
517 described (Honegger et al., 2019). Each image stack, corresponding to a single odor panel
518 delivery, was processed individually. Time-varying voxel fluorescence values for each odor
519 delivery were concatenated to yield a voxel-by-time matrix consisting of each voxel's recorded
520 value during the course of all 13 odor deliveries of the odor panel. After z-scoring, principal
521 component analysis was performed on this matrix and 75% of the variance was retained. Next, *k*-
522 means (k=80, 50 replicates with random starting seeds) was performed to produce 50 distinct
523 voxel cluster assignment maps which we next used to calculate a consensus map. This approach
524 was more accurate than clustering based on a single *k*-means seed.
525
526 Of the 50 generated voxel cluster assignment maps, the top 5 were selected by choosing those
527 maps with the lowest average within-cluster sum of distances, selecting for compact glomeruli.
528 The remaining maps were discarded. Next, all isolated voxel islands in each of the top 5 maps
529 were identified and pruned based on size (minimum size = 100 voxels, maximum size = 10000
530 voxels). Finally, consensus clusters were calculated by finding voxel islands with significant
531 overlap across all 5 of the pruned maps. Voxels which fell within a given cluster across all 5
532 pruned maps were added to the consensus cluster. This process was repeated for all clusters until
533 the single consensus cluster map was complete. In some cases we found by manual inspection
534 that some individual glomeruli were clearly split into two discrete clusters. These splits were
535 remedied by automatically merging all consensus clusters whose centroids were separated by a
536 physical distance of less than 30 voxels and whose peak odor response Spearman correlation was
537 greater than 0.8. Finally, glomeruli were manually labeled based on anatomical position,
538 morphology, and size (Grabe et al., 2015). We focused our analysis on 5 glomeruli (DM1, DM2,
539 DM3, DL5, and DC2), which were the only glomeruli that could be observed in all paired
540 behavior-calcium datasets. However, not all 5 glomeruli were identified in all recordings (Figure
541 1 – figure supplement 3). Missing glomerular data was later mean-imputed.
542
543 ***Calcium image data analysis***
544 All data was processed and analyzed in MATLAB 2018a (Mathworks). Calcium responses for
545 each voxel were calculated as $\Delta f/f = [f(t) - F]/F$, where f(t) and F are the instantaneous and
546 average fluorescence, respectively. Each glomerulus' time-dependent calcium response was
547 calculated as the mean $\Delta f/f$ across all voxels falling within the glomerulus' automatically-
548 generated segmentation mask during a single volume acquisition. Time-varying odor responses
549 were normalized to baseline by subtracting the median of pre-odor $\Delta f/f$ from each trace. Peak
550 odor response was calculated as the maximum fluorescence signal from 7.2s to 10.8s (images 6
551 through 9) of the recording.
552

To compute principal components of calcium dynamics, each fly's complement of odor panel responses (a 5 glomeruli by 13 odors = 65-dimensional vector) was concatenated. Missing glomerulus-odor response values were filled in with the mean glomerulus-odor pair across all fly recordings for which the data was not missing. After infilling, principal component analysis was carried out with individual odor panel deliveries as observations and glomerulus-odor responses pairs as features.

Inter- and intra-fly distances (Figure 1J) were calculated using the projections of each fly's glomerulus-odor responses onto all principal components. For each fly, the average Euclidean distance between response projections 1) among left lobe trials, 2) among right lobe trials, and 3) between left and right lobe trials were averaged together to get a single within-fly distance. Intra-fly distances were computed in a similar fashion (for each fly, taking the average distance of its response projections to those of other flies using only left lobe trials / only right lobe trials / between left-right trials, then averaging these three values to get a single across-fly distance).

In a subset of experiments in which we imaged calcium activity, some solenoids failed to open, resulting in the failure of odor delivery in a small number of trials. In these cases, we identified trials with valve failures by manually recognizing that glomeruli failed to respond during the nominal odor period. These trials were treated as missing data and infilled, as described above. Fewer than ~10% of flies and 5% of odor trials were affected.

For all predictive models constructed, the average principal component score or glomerulus-odor $\Delta f/f$ response across trials was used per individual; that is, each fly contributed one data point to the relevant model. Linear models were constructed from behavior scores and the relevant predictor (principal component, average $\Delta f/f$ across dimensions, specific glomerulus measurements) as described in the text and Tables 1-2. 95% confidence intervals around model regression lines were estimated as +/- 2 standard deviations of the value of the regression line at each x-position across 2000 bootstrap replicates (resampling flies). To predict behavior as a function of time during odor delivery, we analyzed data as described above, but considered only $\Delta f/f$ at each single time point (Figure 4 – figure supplement 2A-C), rather than averaging during the peak response interval.

To decode individual identity from neural responses, we first performed PCA on individual odor panel peak responses. We retained principal component scores constituting specified fractions of variance (Figure 1 – figure supplement 5A) and trained a linear logistic classifier to predict individual identity from single odor panel deliveries.

To decode odor identity from neural responses, each of the 5 recorded glomeruli were used as features, and the calcium response of each glomerulus to a specific odor at a specified time point were used as observations (PNs, n=5317 odor deliveries; ORNs, n=2704 odor deliveries). A

linear logistic classifier was trained to predict the known odor identity using 2-fold cross-validation. That is, a model was trained on half the data and evaluated on the remaining half, and then this process was repeated with the train and test half reversed. The decoding accuracy was quantified as the fraction of odor deliveries in which the predicted odor was correct.

Inference of correlation between latent calcium and behavior states

We performed a simulation-based analysis to infer the strength of the correlation between latent calcium (Brp) and behavior states, given the R^2 of a given linear model. Figure 4 – figure supplement 1A is a schematic of the data generation process we assume underlies our observed data. We assume that the "true" behavioral and calcium values of the animal are captured by unobserved latent states X_c and X_b, respectively, such that the correlation between X_c and X_b is the biological signal captured by the model, having adjusted for the noise associated with actually measuring behavior and calcium (ρ_{signal}). Our calcium and odor preference scores are subject to measurement error and temporal instability (behavior and neural activity were measured 1-3 hours apart). These effects are both noise with respect to estimating the linear relationship between calcium and behavior. Their magnitude can be estimated using the empirical repeatability of behavior and calcium experiments respectively. Thus, our overall approach was to assume true latent behavior and calcium signals that are correlated at the level ρ_{signal}, add noise to them commensurate with the repeatability of these measures to simulate measured behavior and calcium, and record the simulated empirical R^2 between these measured signals. This was done many times to estimate distributions of empirical R^2 given ρ_{signal}. These distributions could finally be used in the inverse direction to infer ρ_{signal} given the actual model R^2 values computed in our study.

Specifically, we simulated X_c as a set of N standard normal variables (N equalling the number of flies used to compute a correlation between predicted and measured preference) and generated $X_b = \rho_{signal} X_c + (1-\rho_{signal}^2 Z)^{½}$, where Z is a set of N standard normal variables uncorrelated with X_c, a procedure that ensures that $corr(X_c, X_b) = \rho_{signal}$. Next, we simulated observed calcium readouts X_c' and X_c'', such that $corr(X_c, X_c') = corr(X_c, X_c'') = r_c$. Similarly, we simulated noisy observed behavioral assay readouts X_b' and X_b'', such that $corr(X_b, X_b') = corr(X_b, X_b'') = r_b$. The values of r_c and r_b were fixed by the empirical repeatability of calcium ($R_{c,c}^2$) and behavior ($R_{b,b}^2$) respectively as follows. Since calcium is a multidimensional measure, and our calcium model predictors are based on principal components of glomerulus-odor responses, we used variance explained along the PCs to calculate a single value for the calcium repeatability $R_{c,c}^2$. We compared the eigenvalues of the real calcium PCA to those of shuffled calcium data (shuffling glomerulus/odor responses for each individual fly), computing $R_{c,c}^2$ by summing the variance explained along the PCs of the calcium data up until the component-wise variance for the calcium data fell below that of the shuffled data, a similar approach as done in Berman et al., 2014 and Werkhoven et al., 2021. $R_{c,c}^2$ was calculated to be 0.77 for both ORN and PN calcium; we set $r_c = (R_{c,c}^2)^{1/4}$ to ensure $corr(X_c', X_c'')^2 = R_{c,c}^2$. We matched r_b to the repeatability across

odor preference trials in the same flies measured 3h apart ($R_{b,b}^2$ =0.23 for OCT vs AIR, and 0.12 for OCT vs MCH, Figure 1 – figure supplement 1B-D), setting $r_b = (R_{b,b}^2)^{1/4}$ to ensure $corr(X_b', X_b'')^2 = R_{b,b}^2$.

We varied ρ_{signal} from 0 to 1 in increments of 0.01, and for each ρ_{signal}, we simulated a set of N X_c and generated X_b, X_c', X_c'', X_b', and X_b'', then we computed a simulated observed calcium-behavior relationship strength $R_{c,b}^2 = corr(X_c', X_b')^2$. We repeated this simulation 10,000 times for each ρ_{signal} and plotted the resultant relationship between ρ_{signal} against $R_{c,b}^2$ (percentiles of $R_{c,b}^2$ are displayed in Figure 4 – figure supplement 1B). Then, for each linear model of interest, we inferred ρ_{signal} by extracting the marginal distribution of ρ_{signal} near the model's R^2 (+/- 20%) and report the median ρ_{signal}.

The procedure outlined above was done analogously for models using Brp-short relative fluorescence intensity, performing the PCA-based calcium response repeatability step with PCA on the multidimensional Brp-short relative fluorescence intensity (which yielded $R_{brp,brp}^2$ = 0.75).

DoOR data

DoOR data for the glomeruli and odors relevant to our study was downloaded from http://neuro.uni-konstanz.de/DoOR/default.html (Münch and Galizia, 2016).

Yoked odor experience experiments

We selected six flies for which both odor preference and neural activity were recorded to serve as the basis for imposed odor experiences for yoked control flies. The experimental flies were chosen to represent a diversity of preference scores. Each experimental fly's odor experience was binned into discrete odor bouts to represent experience of either MCH or OCT based on its location in the tunnel as a function of time (Figure 2J). Odor bouts lasting less than 100 ms were omitted due to limitations on odor-switching capabilities of the odor delivery apparatus. To deliver a given experimental fly's odor experience to yoked controls, we set both odor streams (on either end of the tunnel apparatus) to deliver the same odor experienced by the experimental fly at that moment during the odor-on period. No odor was delivered to yoked controls during time points in which the experimental fly resided in the tunnel choice zone (central 5 mm). See Figure 2J for an example pair of experimental fly and yoked control behavior and odor experience.

Immunohistochemistry

After measuring odor preference behavior, 7-15 day-old flies were anesthetized on ice and brains were dissected in phosphate buffered saline (PBS). Dissection and immunohistochemistry were carried out as previously reported (Wu and Luo, 2006). The experimenter was blind to the behavioral scores of all individuals throughout dissection, imaging, and analysis. Individual

673 identities were maintained by fixing, washing, and staining each brain in an individual 0.2 mL
674 PCR tube using fluid volumes of 100 uL per brain (Fisher Scientific). Primary incubation
675 solution contained mouse anti-nc82 (1:40, DSHB), chicken anti-GFP (1:1000, Aves Labs), rabbit
676 anti-mStrawberry (1:1000, biorbyt), and 5% normal goat serum (NGS, Invitrogen) in PBT (0.5%
677 Triton X-100 in PBS). Secondary incubation solution contained Atto 647N-conjugated goat anti-
678 mouse (1:250, Millipore Sigma), Alexa Fluor 568-conjugated goat anti-rabbit (1:250), Alexa
679 Fluor 488-conjugated goat anti-chicken (1:250, ThermoFisher), and 5% NGS in PBT. Primary
680 and secondary incubation times were 2 and 3 overnights, respectively, at 4° C. Stained samples
681 were mounted and cleared in Vectashield (H-1000, Vector Laboratories) between two coverslips
682 (12-568B, Fisher Scientific). Two reinforcement labels (5720, Avery) were stacked to create a
683 0.15 mm spacer.
684
685 ***Expansion microscopy***
686 Immunohistochemistry for expansion microscopy was carried out as described above, with the
687 exception that antibody concentrations were modified as follows: mouse anti-nc82 (1:40),
688 chicken anti-GFP (1:200), rabbit anti-mStrawberry (1:200), Atto 647N-conjugated goat anti-
689 mouse (1:100), Alexa Fluor 568-conjugated goat anti-rabbit (1:100), Alexa Fluor 488-conjugated
690 goat anti-chicken (1:100). Expansion of stained samples was performed as previously described
691 (Asano et al., 2018; Gao et al., 2019). Expanded samples were mounted in coverslip-bottom petri
692 dishes (MatTek Corporation) and anchored by treating the coverslip with poly-l-lysine solution
693 (Millipore Sigma) as previously described (Asano et al., 2018).
694
695 ***Confocal imaging***
696 All confocal imaging was carried out at the Harvard Center for Biological Imaging. Unexpanded
697 samples were imaged on an LSM700 (Zeiss) inverted confocal microscope equipped with a 40x
698 oil-immersion objective (1.3 NA, EC Plan Neofluar, Zeiss). Expanded samples were imaged on
699 an LSM880 (Zeiss) inverted confocal microscope equipped with a 40x water-immersion
700 objective (1.1 NA, LD C-Apochromat, Zeiss). Acquisition of Z-stacks was automated with Zen
701 Black software (Zeiss).
702
703 ***Standard confocal image analysis***
704 We used custom semi-automated code to generate glomerular segmentation masks from confocal
705 z-stacks of unexpanded Orco>Brp-Short brains. Using Matlab, each image channel was median
706 filtered (σ_x, σ_y, σ_z = 11, 11, 1 pixels) and downsampled in x and y by a factor of 11. Next, an
707 ORN mask was generated by multiplying and thresholding the Orco>mCD8 and Orco>Brp-Short
708 channels. Next, a locally normalized nc82 and Orco>mCD8 image stack were multiplied and
709 thresholded, and the ORN mask was applied to remove background and other undesired brain
710 structures. This pipeline resulted in a binary image stack which maximized the contrast of the
711 glomerular structure of the antennal lobe. We then applied a binary distance transform and

712 watershed transform to generate discrete subregions which aimed to represent segmentation
713 masks for each glomerulus tagged by Orco-Gal4.
714
715 However, this procedure generally resulted in some degree of under-segmentation; that is, some
716 glomerular segmentation masks were merged. To split each merged segmentation mask, we
717 convolved a ball (whose radius was proportional to the cube root of the volume of the
718 segmentation mask in question) across the mask and thresholded the resulting image. The
719 rationale of this procedure was that 2 merged glomeruli would exhibit a mask shape resembling
720 two touching spheres, and convolving a similarly-sized sphere across this volume followed by
721 thresholding would split the merged object. After ball convolution, we repeated the distance and
722 watershed transform to once more generate discrete subregions representing glomerular
723 segmentation masks. This second watershed step generally resulted in over-segmentation; that is,
724 by visual inspection it was apparent that many glomeruli were split into multiple subregions.
725 Therefore, we finally manually agglomerated the over-segmented subregions to generate single
726 segmentation masks for each glomerulus of interest. We used a published atlas to aid manual
727 identification of glomeruli (Grabe et al., 2015). The total Brp-Short fluorescence signal within
728 each glomerulus was determined and divided by the volume of the glomerulus' segmentation
729 mask to calculate Brp-Short density values.
730
731 ***Expansion microscopy image analysis***
732 The spots function in Imaris 9.0 (Bitplane) was used to identify individual Brp-Short puncta in
733 expanded sample image stacks of Or13a>Brp-Short samples (Mosca and Luo, 2014). The spot
734 size was set to 0.5 um, background subtraction and region-growing were enabled, and the default
735 spot quality threshold was used for each image stack. Identified spots were used to mask the Brp-
736 Short channel and the resultant image was saved as a new stack. In MATLAB, a glomerular
737 mask was generated by smoothing (σ_x, σ_y, σ_z = 40, 40, 8 pixels) and thresholding (92.5th
738 percentile) the raw Brp-Short image stack. The mask was then applied to the spot image stack to
739 remove background spots. Finally, the masked spot image stack was binarized and spot number
740 and properties were quantified.
741
742 ***Antennal Lobe modeling***
743 We constructed a model of the antennal lobe to test the effect of circuit variation on PN activity
744 variation across individuals. Our general approach to producing realistic circuit activity with the
745 AL model was 1) using experimentally-measured parameters whenever possible (principally the
746 connectome wiring diagram and biophysical parameters measured electrophysiologically), 2)
747 associating free parameters only with biologically plausible categories of elements, while
748 minimizing their number, and 3) tuning the model using those free parameters so that it
749 reproduced high-level patterns of activity considered in the field to represent the canonical
750 operations of the AL. Simulations were run in Python (version 3.6) (van Rossum and Drake,
751 2011), and model outputs were analyzed using Jupyter notebooks (Kluyver et al., 2016) and

Python and Matlab scripts.

AL model neurons

Release 1.2 of the hemibrain connectomics dataset (Scheffer et al., 2020) was used to set the connections in the model. Hemibrain body IDs for ORNs, LNs, and PNs were obtained via the lists of neurons supplied in the supplementary tables in Schlegel et al., 2020. ORNs and PNs of non-olfactory glomeruli (VP1d, VP1l, VP1m, VP2, VP3, VP4, VP5) were ignored, leaving 51 glomeruli. Synaptic connections between the remaining 2574 ORNs, 197 LNs, 166 mPNs, and 130 uPNs were queried from the hemibrain API. All ORNs were assigned to be excitatory (Wilson, 2013). Polarities were assigned to PNs based on the neurotransmitter assignments in Bates et al., 2020. mPNs without neurotransmitter information were randomly assigned an excitatory polarity with probability equal to the fraction of neurotransmitter-identified mPNs that are cholinergic; the same process was performed for uPNs. After confirming that the model's output was qualitatively robust to which mPNs and uPNs were randomly chosen, this random assignment was performed once and then frozen for subsequent analyses.

Of the 197 LNs, we assigned 31 to be excitatory, based on the estimated 1:5.4 ratio of eLNs to iLNs in the AL (Tsai et al., 2018). To account for observations that eLNs broadly innervate the AL (Shang et al., 2007), all LNs were ranked by the number of innervated glomeruli, and the 31 eLNs were chosen uniformly at random from the top 50% of LNs in the list. This produced a distribution of glomerular innervations in eLNs qualitatively similar to that of *krasavietz* LNs in Supplementary Figure 6 of Chou et al., 2010.

Voltage model

We used a single-compartment leaky-integrate-and-fire voltage model for all neurons as in Kakaria and de Bivort, 2017, in which each neuron had a voltage $V_i(t)$ and current $I_i(t)$. When the voltage of neuron i was beneath its threshold $V_{i,\,thr}$, the following dynamics were obeyed:

$$C_i \frac{dV_i}{dt} = \frac{V_{i,0} - V_i(t)}{R_i} + I_{i,odor}(t) + \sum_{j=1}^{N} a_i W_{ji} I_j(t)$$

Each neuron i had electrical properties: membrane capacitance C_i, resistance R_i, and resting membrane potential $V_{i,0}$ with values from electrophysiology measurements (Table 2).

When the voltage of a neuron exceeded the threshold $V_{i,\,thr}$, a templated action potential was filled into its voltage time trace, and a templated postsynaptic current was added to all downstream neurons, following the definitions in Kakaria and de Bivort, 2017.

Odor stimuli were simulated by triggering ORNs to spike at frequencies matching known olfactory receptor responses to the desired odor. The timing of odor-evoked spikes was given by

a Poisson process, with firing rate *FR* for ORNs of a given glomerulus governed by:

$$FR_{glom,odor}(t) = FR_{max} D_{glom,odor}(f_a + (1 - f_a)e^{-t/t_a})$$

FR_{max}, the maximum ORN firing rate, was set to 400 Hz. $D_{glom,\,odor}$ is a value between 0 and 1 from the DoOR database, representing the response of an odorant receptor/glomerulus to an odor, estimated from electrophysiology and/or fluorescence data (Münch and Galizia, 2016). ORNs display adaptation to odor stimuli (Wilson, 2013), captured by the final term with timescale t_a = 110 *ms* to 75% of the initial value, as done in Kao and Lo, 2020. Thus, the functional maximum firing rate of an ORN was 75% of 400 Hz = 300 Hz, matching the highest ORN firing rates observed experimentally (Hallem et al., 2004). After determining the times of ORN spikes according to this firing-rate rule, spikes were induced by the addition of 10^6 picoamps in a single time step. This reliably triggered an action potential in the ORN, regardless of currents from other neurons. In the absence of odors, spike times for ORNs were drawn by a Poisson process at 10 Hz, to match reported spontaneous firing rates (de Bruyne et al., 2001).

For odor-glomeruli combinations with missing DoOR values (40% of the dataset), we performed imputation via alternating least squares (using the pca function with option 'als' to infill missing values (MATLAB documentation) on the odor x glomerulus matrix 1000 times and taking the mean infilled matrix, which provides a closer match to ground truth missing values than a single run of ALS (Figure 1 – figure supplement 5 of Werkhoven et al., 2021).

A neuron *j* presynaptic to *i* supplies its current $I_j(t)$ scaled by the synapse strength W_{ji}, the number of synapses in the hemibrain dataset from neuron *j* to *i*. Rows in *W* corresponding to neurons with inhibitory polarity (i.e. GABAergic PNs or LNs) were set negative. Finally, post-synaptic neurons (columns of the connectivity matrix) have a class-specific multiplier a_i, a hand-tuned value, described below.

AL model tuning

Class-specific multiplier current multipliers (a_i) were tuned using the panel of 18 odors from Bhandawat et al., 2007 (our source for several experimental observations of high-level AL function): benzaldehyde, butyric acid, 2,3-butanedione, 1-butanol, cyclohexanone, Z3-hexenol, ethyl butyrate, ethyl acetate, geranyl acetate, isopentyl acetate, isoamyl acetate, 4-methylphenol, methyl salicylate, 3-methylthio-1-propanol, octanal, 2-octanone, pentyl acetate, E2-hexenal, trans-2-hexenal, gamma-valerolactone. Odors were "administered" for 400 ms each, with 300 ms odor-free pauses between odor stimuli.

The high-level functions of the AL that represent a baseline, working condition were: (1) firing rates for ORNs, LNs, and PNs matching the literature (listed in Table 2 and see (Bhandawat et al., 2007; Dubin and Harris, 1997; Jeanne and Wilson, 2015; Seki et al., 2010), (2) a more

uniform distribution of PN firing rates during odor stimuli compared to ORN firing rates, (3) greater separation of representations of odors in PN-coding space than in ORN-coding space, and (4) a sublinear transfer function between ORN firing rates and PN firing rates. Features (2) - (4) relate to the role of the AL in enhancing the separability of similar odors (Bhandawat et al., 2007).

To find a parameterization with those functions, we tuned the values of a_i as scalar multipliers on ORN, eLN, iLN, and PN columns of the hemibrain connectivity matrix. Thus, these values represent cell type-specific sensitivities to presynaptic currents, which may be justified by the fact that ORNs/LNs/PNs are genetically distinct cell populations (McLaughlin et al., 2021; Xie et al., 2021). A grid search of the four class-wise sensitivity parameters produced a configuration that reasonably satisfied the above criteria (Figure 5 – figure supplement 2). In this configuration, the ORN columns of the hemibrain connectivity matrix are scaled by 0.1, eLNs by 0.04, iLNs by 0.02, and PNs by 0.4. The relatively large multiplier on PNs is potentially consistent with the fact that PNs are sensitive to small differences between weak ORN inputs (Bhandawat et al., 2007). Model outputs were robust over several different sets of a_i, provided iLN sensitivity $\simeq$ eLN < ORN < PN.

We analyzed the sensitivity of the model's parameters around their baseline values of a_{ORN}, a_{eLN}, a_{iLN}, a_{PN} = (0.1, 0.04, 0.02, 0.4). Each parameter was independently scaled up to 4x or 1/4x of its baseline value (Figure 5 – figure supplement 3), and the PN firing rates recorded. Separately, multiple-parameter manipulations were performed by multiplying each parameter by a random log-Normal value with mean 1 and +/-1 standard deviation corresponding to a 2x or 0.5x scaling on each parameter. Mean PN-odor responses were calculated for all manipulated runs and compared to the mean PN-odor responses for the baseline configuration. A manipulation effect size was calculated by cohen's *d* ((mean manipulated response - mean baseline response)/(pooled standard deviation)). None of these manipulations reached effect size magnitudes larger than 0.9 (which can be roughly interpreted as the number of standard deviations in the baseline PN responses away from the mean baseline PN response), which signaled that the model was robust to the sensitivity parameters in this range. The most sensitive parameter was, unsurprisingly, a_{PN}.

Notable ways in which the model behavior deviates from experimental recordings (and thus caveats on the interpretation of the model) include: 1) Model LNs appear to have more heterogeneous firing rates than real LNs, with many LNs inactive for this panel of odor stimuli. This likely reflects a lack of plastic/homeostatic mechanisms in the model to regularize LN firing rates given their variable synaptic connectivity (Chou et al., 2010). 2) Some PNs had off-odor rates that are high compared to real PNs, resulting in a distribution of ON-OFF responses that had a lower limit than in real recordings. Qualitatively close matches were achieved between the model and experimental data in the distributions of odor representations in ORN vs PN spaces and the non-linearity of the ORN-PN transfer function.

AL model circuit variation generation

We generated AL circuit variability in two ways: cell-type bootstrapping, and synapse density resampling. These methods assume that the distribution of circuit configurations across individual ALs can be generated by resampling circuit components within a single individual's AL (neurons and glomerular synaptic densities, respectively, from the hemibrain EM volume).

To test the effect of variation in the developmental complement of neurons of particular types, we bootstrapped populations of interest from the list of hemibrain neurons. Resampling with replacement of ORNs was performed glomerulus-by-glomerulus, i.e., separately among each pool of ORNs expressing a particular *Odorant receptor* gene. The same was done for PNs. For LNs, all 197 LNs were treated as a single pool; there was no finer operation based on LN subtypes or glomerular innervations. This choice reflects the high developmental variability of LNs (Chou et al., 2010). The number of synapses between a pair of bootstrapped neurons was equal to the synapse count between those neurons in the hemibrain connectivity matrix.

In some glomeruli, bootstrapping PNs produced unreasonably high variance in the total PN synapse count. For instance, DP1m, DC4, and DM3 each harbor PNs that differ in total synapse count by a factor of ~10. Since these glomeruli have between two to three PNs each, in a sizable proportion of bootstrap samples, all-highly connected (or all-lowly) connected PNs are chosen in such glomeruli. To remedy this biologically unrealistic outcome, we examined the relationship between total input PN synapses within a glomerulus and glomerular volume (Figure 5 – figure supplement 4). In the "synapse density resampling" method, we required that the number of PN input synapses within a glomerulus reflect a draw from the empirical relationship between total input PN synapses and glomerular volume as present in the hemibrain data set. This was achieved by, for each glomerulus, sampling from the following distribution that depends on glomerular volume, then multiplying the number of PN input synapses by a scalar to match that sampled value:

$$log\ S_g\ = log\ (a\ V_g{}^d)\ +\ \varepsilon_g, \varepsilon_g\ \sim N(0, \sigma^2)$$

Here S_g is the PN input synapse count for glomerulus g, V_g is the volume of glomerulus g (in cubic microns), ε is a Gaussian noise variable with standard deviation σ, and a, d are the scaling factor and exponent of the volume term, respectively. The values of these parameters (a = 8.98, d = 0.73, σ = 0.38) were fit using maximum likelihood.

Quantification and statistical analysis

All fly behavior and calcium data was processed and analyzed in MATLAB 2018a (Mathworks). AL simulations were run in Python (version 3.6) (van Rossum and Drake, 2011), and model outputs were analyzed using Jupyter notebooks (Kluyver et al., 2016) and Python scripts. We

911 performed a power analysis prior to the study to determine that recording calcium activity in 20-
912 40 flies would be sufficient to identify moderate calcium-behavior correlations. Sample sizes for
913 expansion microscopy were smaller, as the experimental procedure was more involved –
914 therefore, we did not conduct a formal statistical analysis. Linear models were fit using the fitlm
915 MATLAB function (https://www.mathworks.com/help/stats/fitlm.html); coefficients and p-
916 values of models between measured preferences and predicted preferences are listed in Table 1.
917 95% confidence intervals around model regression lines were estimated as +/- 2 standard
918 deviations of the value of the regression line at each x-position across 2000 bootstrap replicates
919 (resampling flies). Boxplots depict the median value (points), interquartile range (boxes), and
920 range of the data (whiskers).
921
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932
933 **Author contributions**
934 M.C. conducted behavior experiments with assistance from M.S., conducted confocal
935 microscopy, and conducted expansion microscopy with contributions from R. G. and E.B. D.L.
936 implemented the computational AL model. B.L.d.B. supervised the project.
937
938 **Declaration of interests**
939 E.B. is a co-founder of a company that aims to commercialize expansion microscopy for medical
940 purposes. R.G. and E.B. are co-inventors on multiple patents related to expansion microscopy.
941 The authors declare no other competing interests.

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Figures and figure supplements

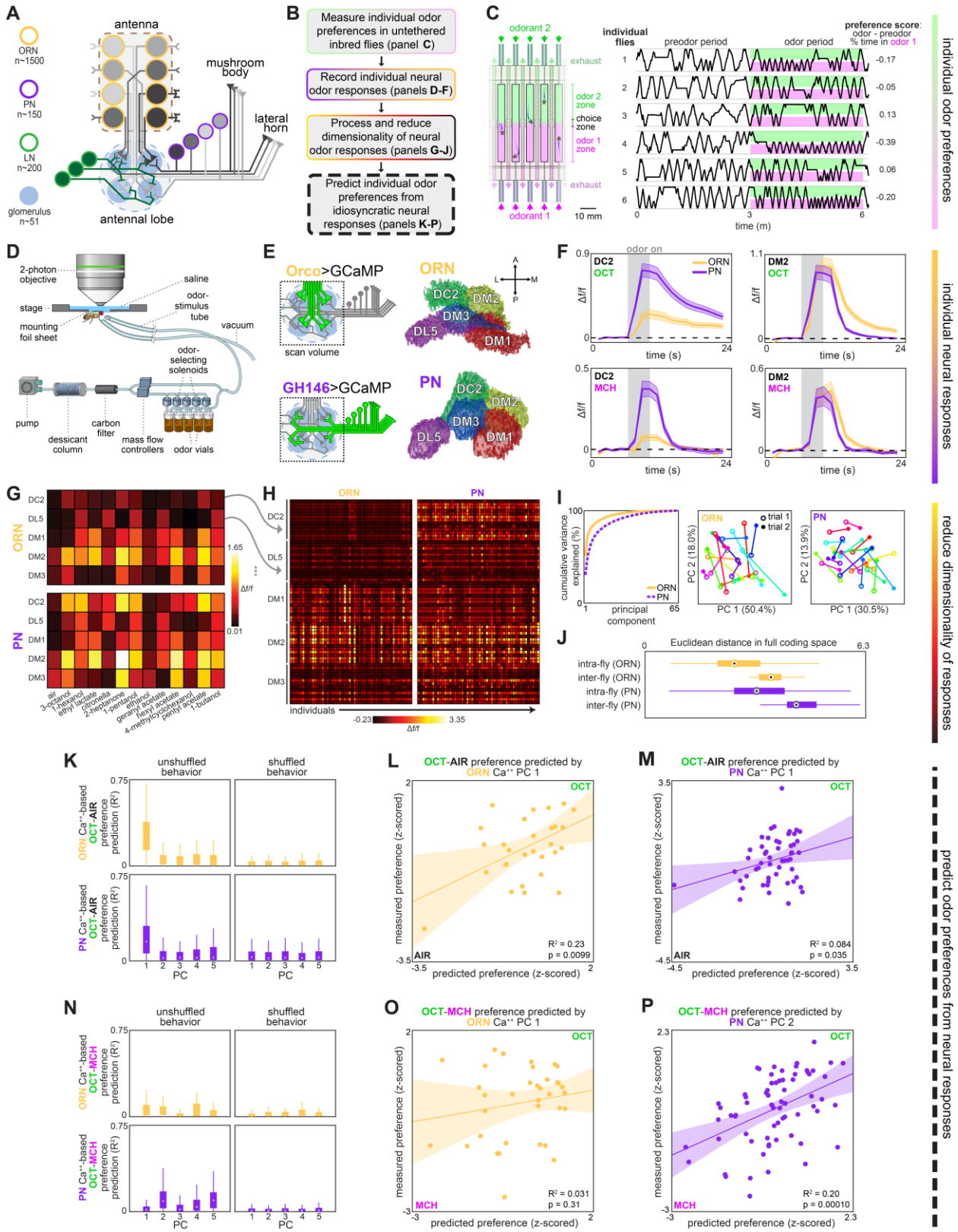


Figure 1. Idiosyncratic calcium dynamics predict individual odor preferences.

(A) Olfactory circuit schematic. Olfactory receptor neurons (ORNs, peach outline) and projection neurons (PNs, plum outline) are comprised of ~51 classes corresponding to odor

receptor response channels. ORNs (gray shading) sense odors in the antennae and synapse on dendrites of PNs of the same class in ball-shaped structures called glomeruli located in the antennal lobe (AL). Local neurons (LNs, green outline) mediate interglomerular cross-talk and presynaptic inhibition, amongst other roles (Olsen and Wilson, 2008; Yaksi and Wilson, 2010). Odor signals are normalized and whitened in the AL before being sent to the mushroom body and lateral horn for further processing. Schematic adapted from Honegger et al., 2019 **(B)** Experiment outline. **(C)** Odor preference behavior tracking setup (reproduced from Honegger, Smith, et al. (Honegger et al., 2019)) and example individual fly ethograms. OCT (green) and MCH (magenta) were presented for 3 minutes. **(D)** Head-fixed 2-photon calcium imaging and odor delivery setup (reproduced from Honegger et al., 2019) **(E)** Orco and GH146 driver expression profiles (left) and example segmentation masks (right) extracted from 2-photon calcium images for a single fly expressing Orco>GCaMP6m (top, expressed in a subset of all ORN classes) or GH146>Gcamp6m (bottom, expressed in a subset of all PN classes). **(F)** Time-dependent $\Delta f/f$ for glomerular odor responses in ORNs (peach) and PNs (plum) averaged across all individuals: DC2 to OCT (upper left), DM2 to OCT (upper right), DC2 to MCH (lower left), and DM2 to OCT (lower right). Shaded error bars represent S.E.M. **(G)** Peak $\Delta f/f$ for each glomerulus-odor pair averaged across all flies. **(H)** Individual neural responses measured in ORNs (left) or PNs (right) for 50 flies each. Columns represent the average of up to 4 odor responses from a single fly. Each row represents one glomerulus-odor response pair. Odors are the same as in panel (G). **(I)** Principal component analysis of individual neural responses. Fraction of variance explained versus principal component number (left). Trial 1 and trial 2 of ORN (middle) and PN (right) responses for 20 individuals (unique colors) embedded in PC 1-2 space. **(J)** Euclidean distances between glomerulus-odor responses within and across flies measured in ORNs (n=65 flies) and PNs (n=122 flies). Distances calculated without PCA compression. Points represent the median value, boxes represent the interquartile range, and whiskers the range of the data. **(K)** Bootstrapped R^2 of OCT-AIR preference prediction from each of the first 5 principal components of neural activity measured in ORNs (top, all data) or PNs (bottom, training set). **(L)** Measured OCT-AIR preference versus preference predicted from PC 1 of ORN activity (n=30 flies). **(M)** Measured OCT-AIR preference versus preference predicted from PC 1 of PN activity in n=53 flies using a model trained on a training set of n=18 flies (see Figure 2 – figure supplement 1A-B for train/test flies analyzed separately). **(N)** Bootstrapped R^2 of OCT-MCH preference prediction from each of the first 5 principal components of neural activity measured in ORNs (top, all data) or PNs (bottom, training set). **(O)** Measured OCT-MCH preference versus preference predicted from PC 1 of ORN activity (n=35 flies). **(P)** Measured OCT-MCH preference versus preference predicted from PC 2 of PN activity in n=69 flies using a model trained on a training set of n=47 flies (see Figure 2 – figure supplement 1C-D for train/test flies analyzed separately). Shaded regions in L,M,O,P are the 95% CI of the fit estimated by bootstrapping.

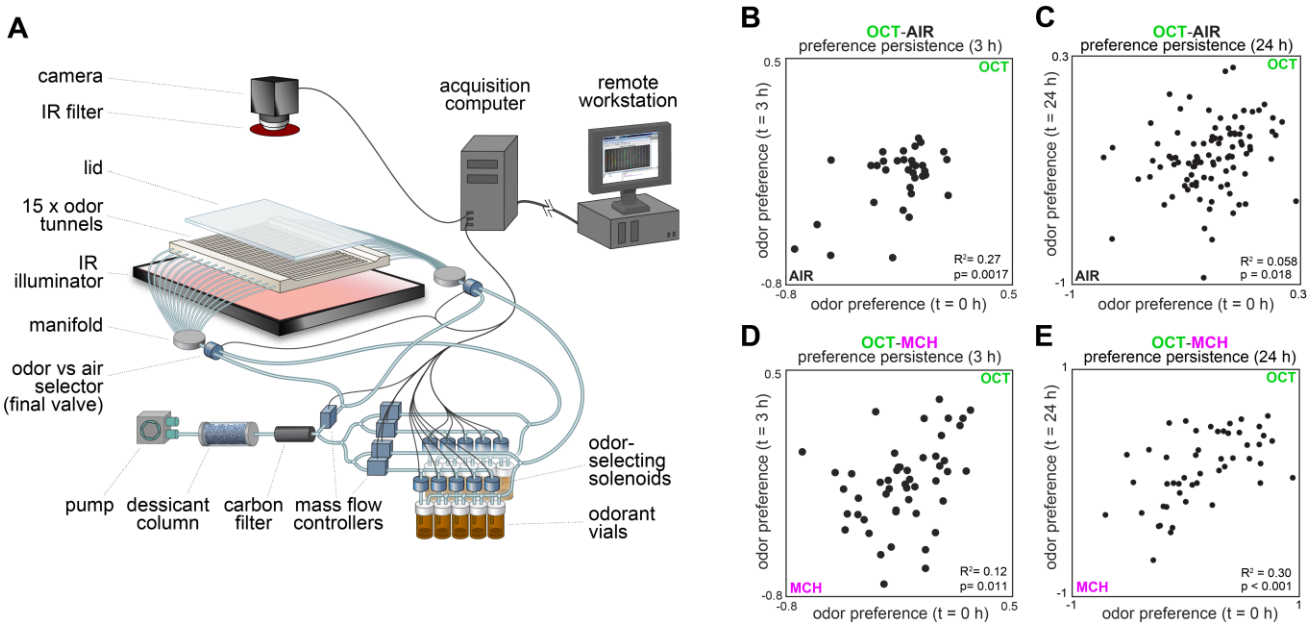


Figure 1 – figure supplement 1. Behavioral measurements and individual preference persistence.

(A) Behavioral measurement apparatus (adapted from Honegger et al., 2019) **(B)** Odor preference persistence over 3 hours for flies given a choice between 3-octanol and air (n=34 flies). **(C)** Odor preference persistence over 24 hours for flies given a choice between 3-octanol and air (n=97 flies). **(D)** Odor preference persistence over 3 hours for flies given a choice between 3-octanol and 4-methylcyclohexanol (n=51 flies). **(E)** Odor preference persistence over 24 hours for flies given a choice between 3-octanol and 4-methylcyclohexanol (n=49 flies).

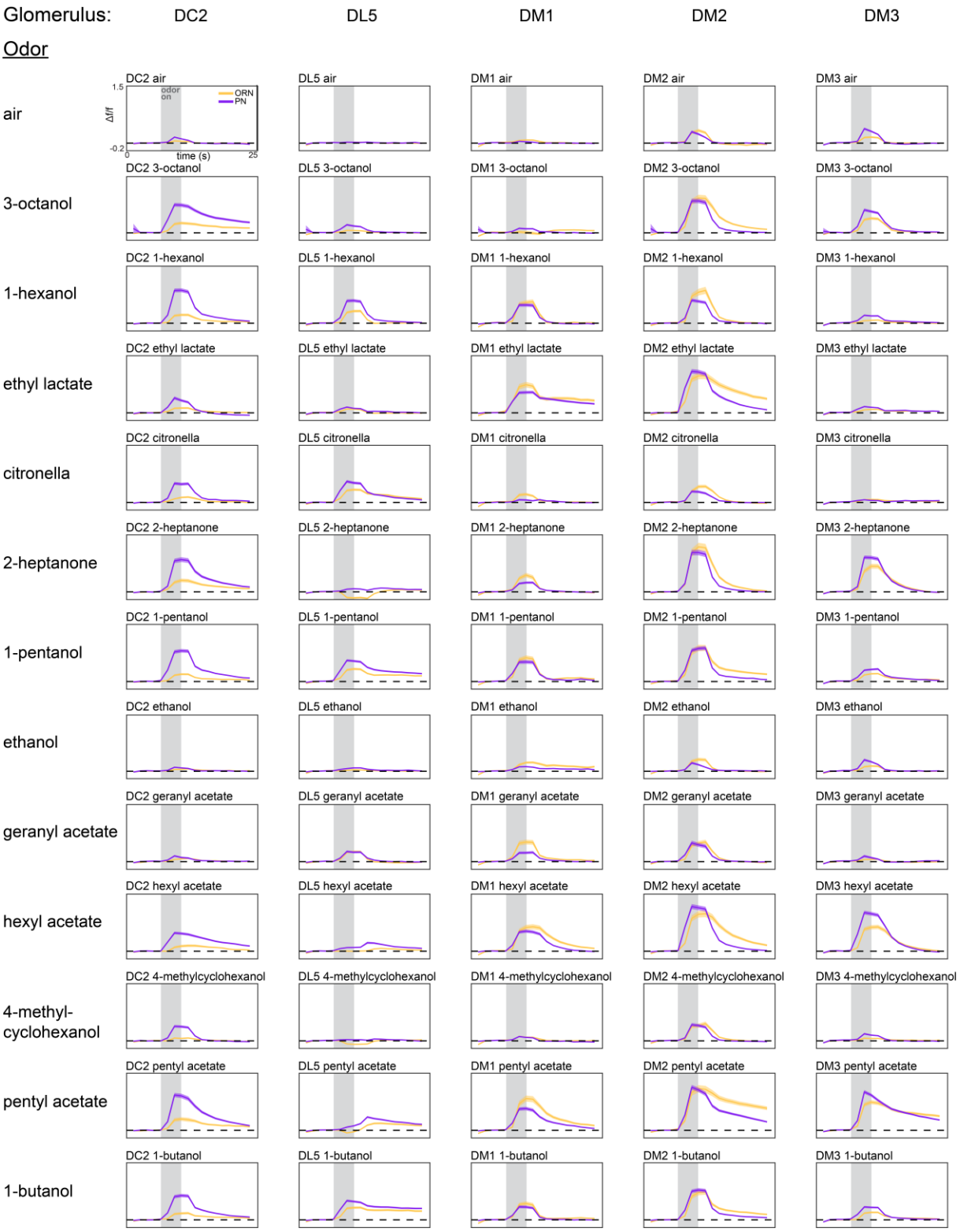


Figure 1 – figure supplement 2. Average glomerulus-odor time-dependent responses.
Time-dependent responses of each glomerulus identified in our study to the 13 odors in our odor panel. Data represents the average across flies (ORN, peach curves, n=65 flies; PN, plum curves, n=122 flies). Shaded error bars represent S.E.M.

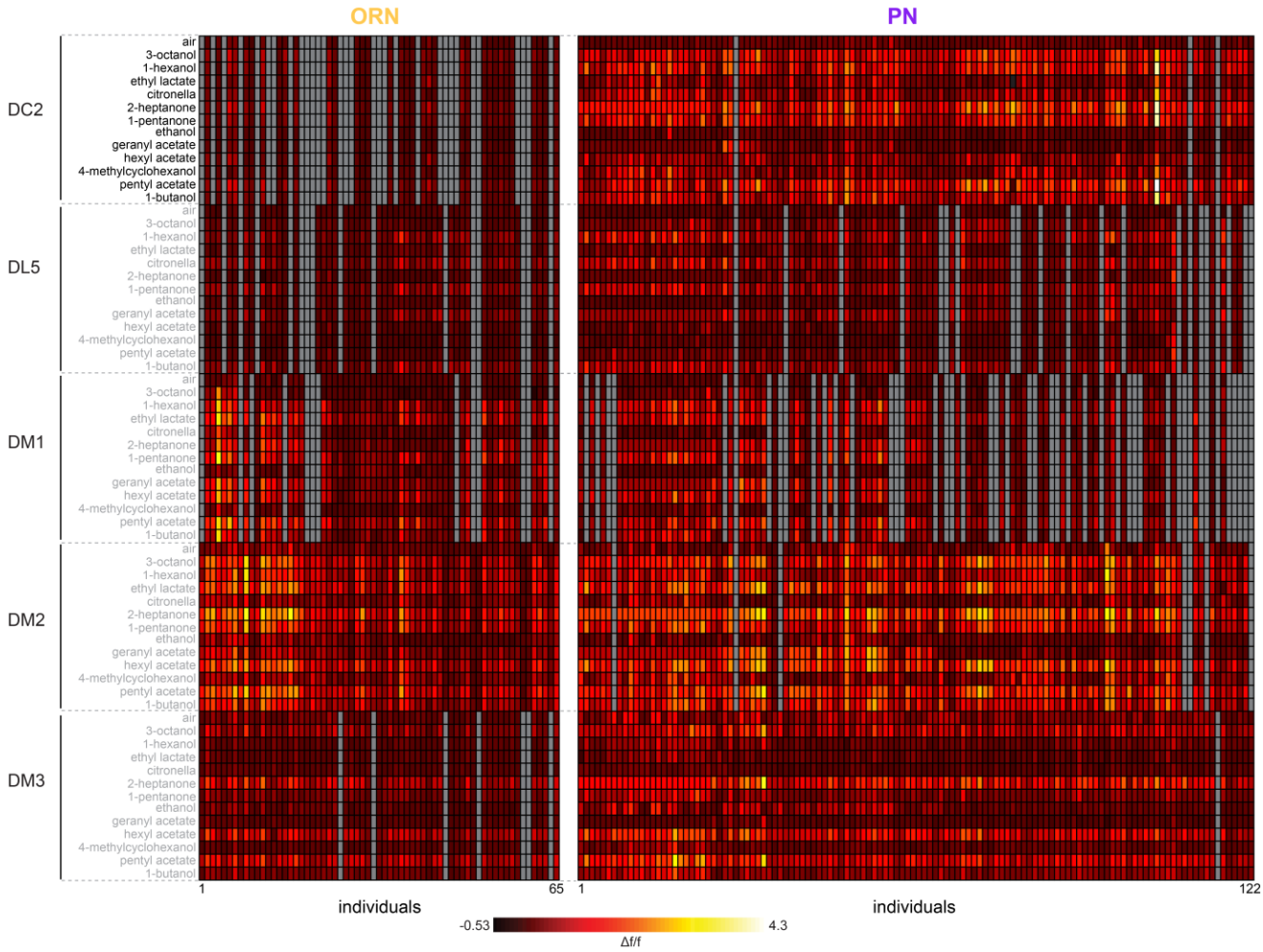


Figure 1 – figure supplement 3. Individual glomerulus-odor responses.
Idiosyncratic odor coding measured in ORNs (left, n=65 flies) and PNs (right, n=122 flies). Each column represents the response (max Δf/f attained over the odor trial) of a single fly averaged over up to 4 odor deliveries. Each row represents a glomerulus-odor response pair. Missing data are indicated in gray.

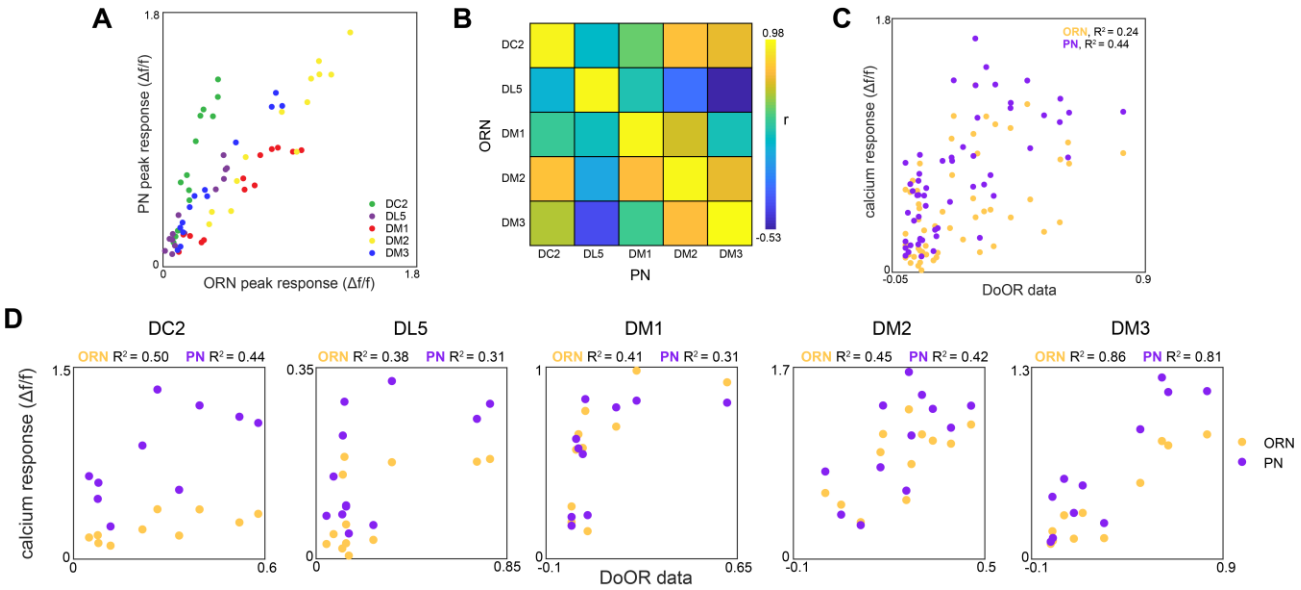


Figure 1 – figure supplement 4. Glomerulus responses and identification.
(A) Glomerulus odor responses measured in PNs versus those measured in ORNs. Points correspond to the odorants listed in Figure 1G. **(B)** Cross-odor trial correlation matrix between glomerular odor responses in ORNs and PNs. **(C)** Peak calcium responses for each glomerulus-odor pair measured in this study plotted against those recorded in the DoOR dataset (Münch and Galizia, 2016). **(D)** Peak calcium responses for each individual glomerulus plotted against those recorded in the DoOR dataset.

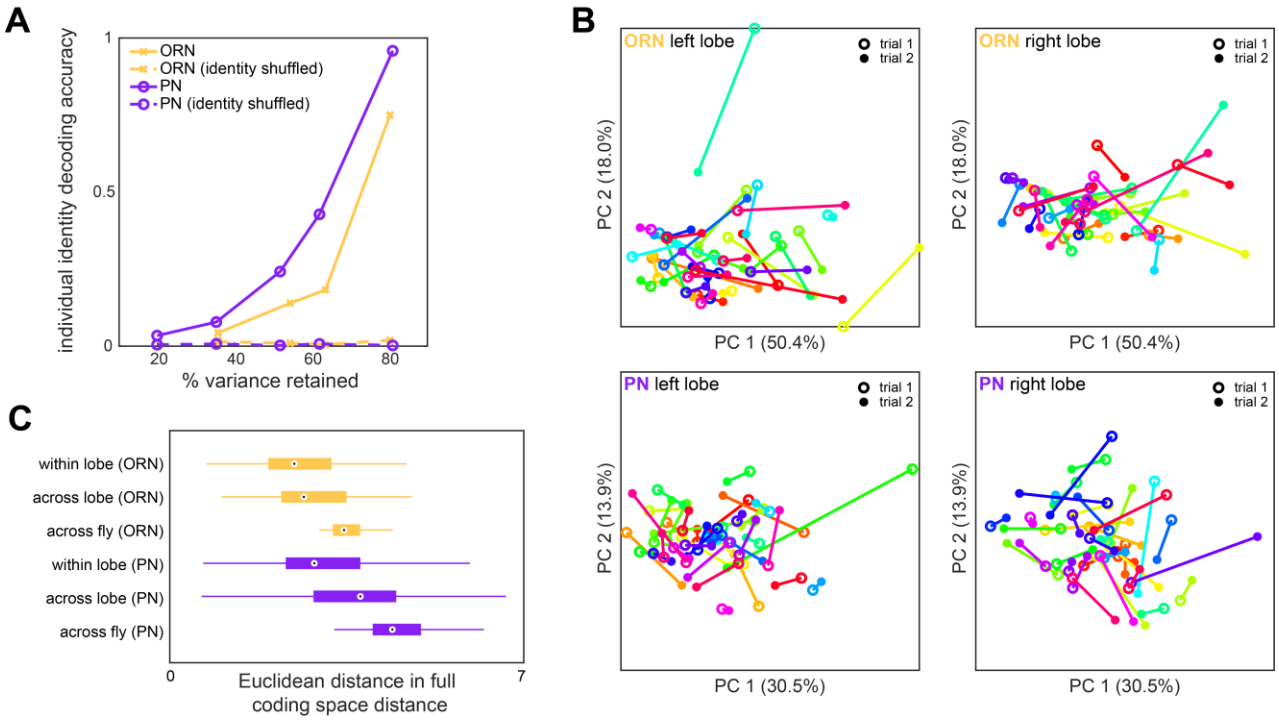


Figure 1 – figure supplement 5. Idiosyncrasy of ORN and PN responses.

(A) Logistic regression classifier accuracy of decoding individual identity from individual odor panel peak responses. PCA was performed on population responses and the specified fraction of variance (x-axis) was retained. Individual identity can be better decoded from PN responses than ORN responses in all cases. **(B)** Individual trial-to-trial glomerulus-odor responses embedded in PC 1-2 space. Responses for the same flies as Figure 1I are shown. Each linked color represents one fly. Trial 1 and trial 2 responses are shown for ORN left lobe (upper left), ORN right lobe (upper right), PN left lobe (lower left), and PN right lobe (lower right). **(C)** Distance in the full glomerulus-odor response space between recordings within a lobe (trial-to-trial), across lobes (within fly), and across flies for ORNs and PNs. Points represent the median value, boxes represent the interquartile range, and whiskers the range of the data.

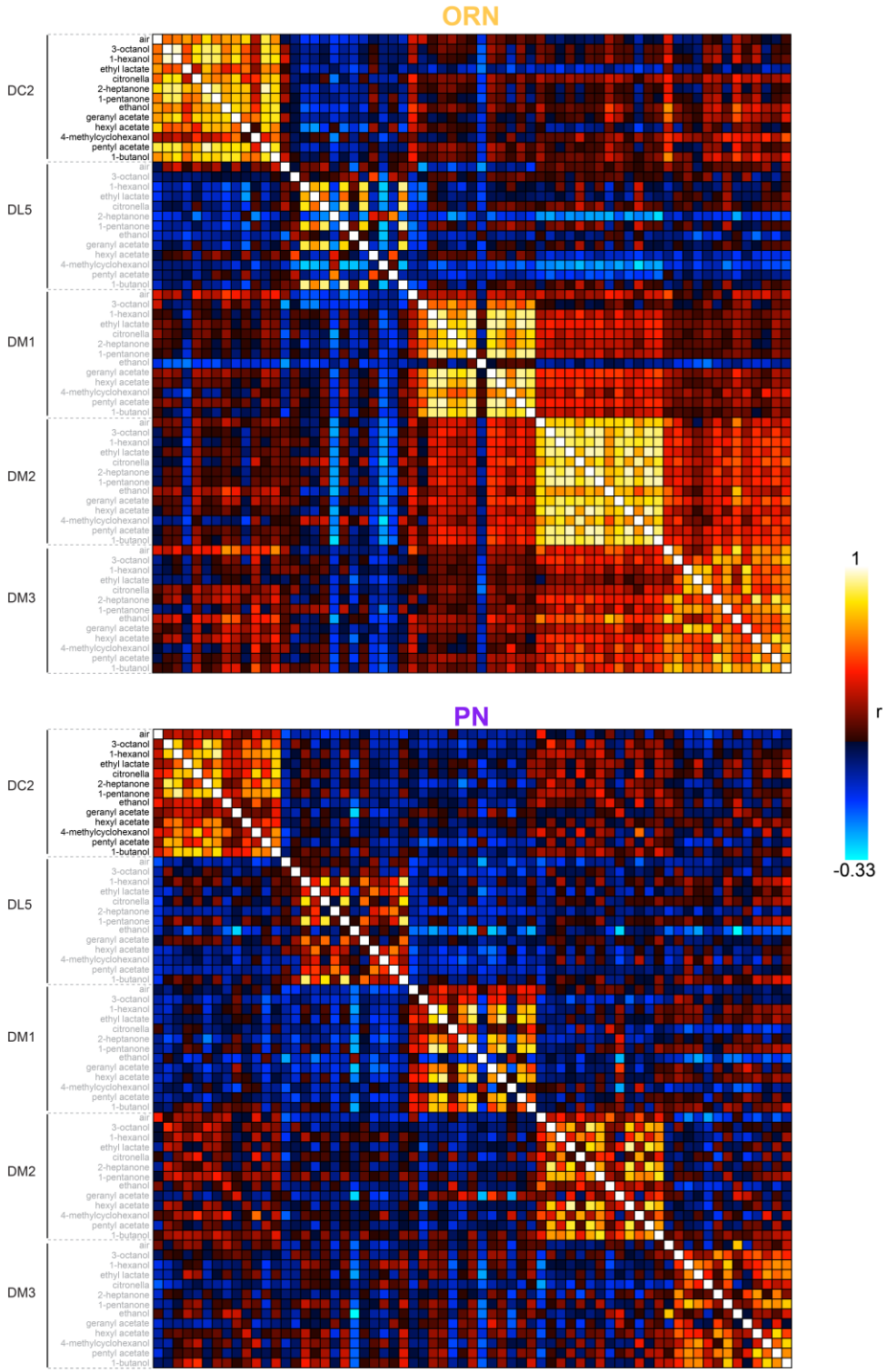


Figure 1 – figure supplement 6. Calcium response correlation matrices.
Correlation between calcium response dimensions across flies measured in ORNs (top) and PNs (bottom). Glomerulus-odor responses are correlated at the level of glomeruli in both cell types. Inter-glomerulus correlations are more prominent in ORNs than PNs, consistent with known AL transformations that result in decorrelated PN activity (Bhandawat et al., 2007; Luo et al., 2010).

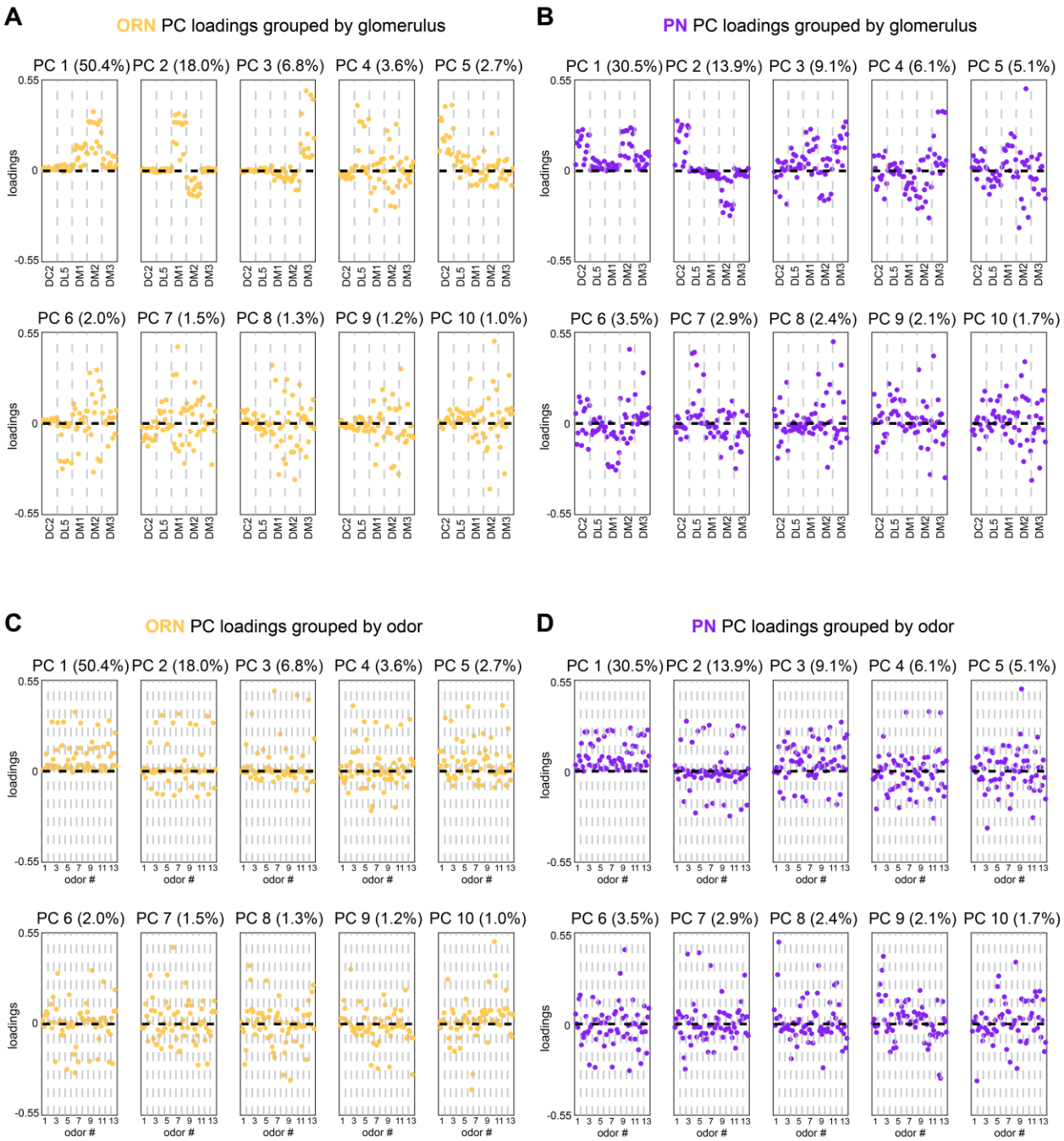


Figure 1 – figure supplement 7. Calcium imaging principal component loadings.

(A-B) First 10 principal component loadings measured from calcium responses in ORNs (A, n=65 flies) and PNs (B, n=122 flies). Loadings are grouped by glomerulus, with each loading within a glomerulus representing the response of that glomerulus to one odor in the odor panel. Odors are the same as those listed in Figure 1G. **(C-D)** The same 10 principal component loadings as those shown in panels (A-B) grouped by odor rather than glomerulus. Glomeruli within each odor block are given in the order of panels (A) and (B).

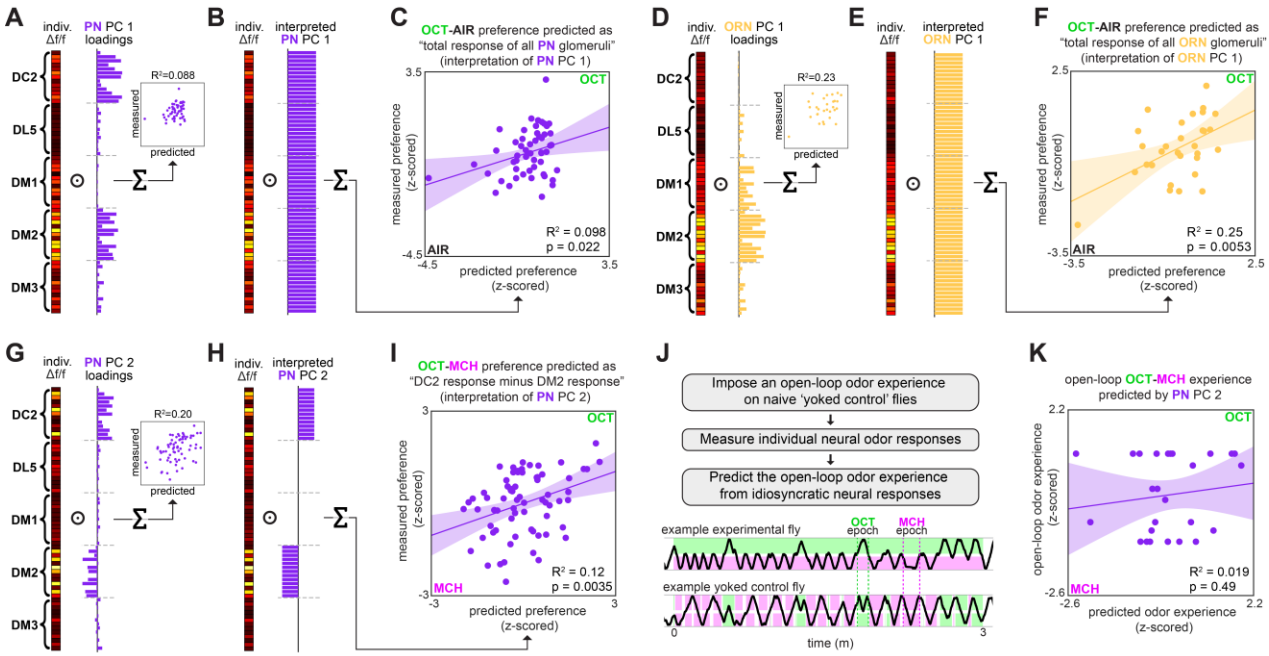


Figure 2. Variation in global and relative glomerular responses explains individual preferences.

(A) PC 1 loadings of PN activity for flies tested for OCT-AIR preference (n=53 flies). **(B)** Interpreted PN PC 1 loadings. **(C)** Measured OCT-AIR preference versus preference predicted by the average peak response across all PN coding dimensions (n=53 flies). **(D)** PC 1 loadings of ORN activity for flies tested for OCT-AIR preference (n=30 flies). **(E)** Interpreted ORN PC 1 loadings. **(F)** Measured OCT-AIR preference versus preference predicted by the average peak response across all ORN coding dimensions (n=30 flies). **(G)** PC 2 loadings of PN activity for flies tested for OCT-MCH preference (n=69 flies). **(H)** Interpreted PN PC 2 loadings. **(I)** Measured OCT-MCH preference versus preference predicted by the average peak PN response in DM2 minus DC2 across all odors (n=69 flies). **(J)** Yoked control experiment outline and example behavior traces. Experimental flies are free to move about tunnels permeated with steady state OCT and MCH flowing into either end. Yoked control flies are delivered the same odor at both ends of the tunnel which matches the odor experienced at the nose of the experimental fly at each moment in time. **(K)** Imposed odor experience versus the odor experience predicted from PC 2 of PN activity (n=27 flies) evaluated on the model trained from data in Figure 1P. Shaded regions in C,F,I,K are the 95% CI of the fit estimated by bootstrapping.

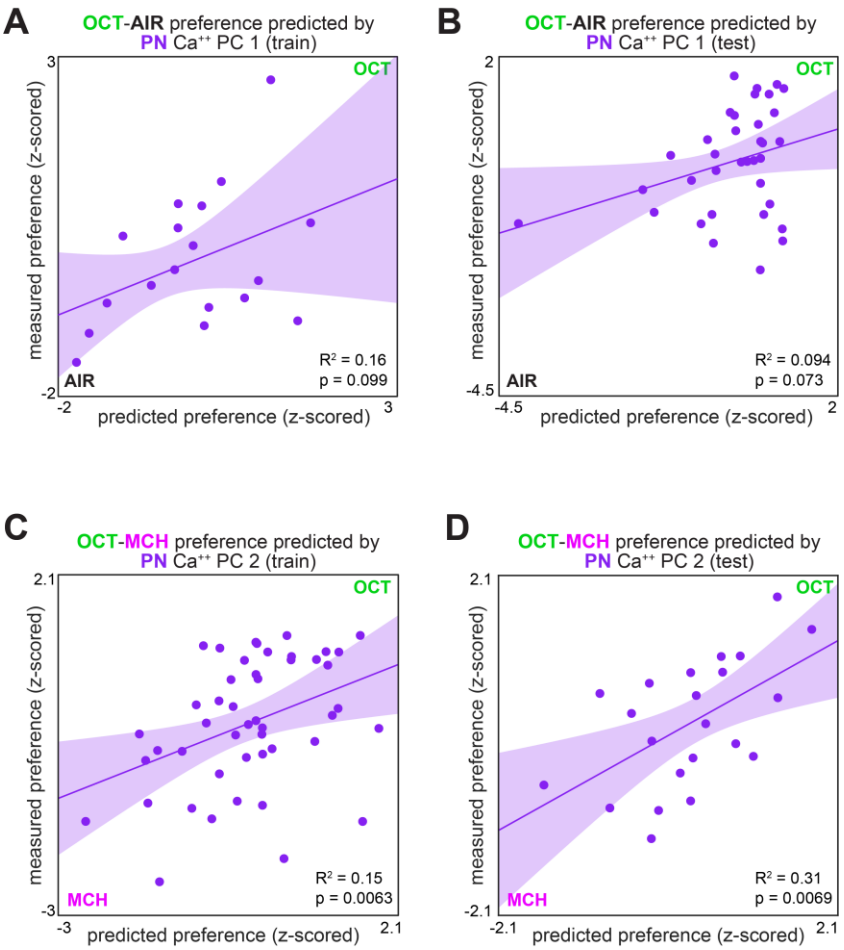


Figure 2 – figure supplement 1. Measured preference vs. PN activity-based predicted preference, split by training/testing set.

(A) Measured OCT-AIR preference versus preference predicted from PC 1 of PN activity in a training set (n=18 flies). **(B)** Measured OCT-AIR preference versus preference predicted from PC 1 on PN activity in a test set (n=35 flies) evaluated on a model trained on data from panel (A). **(C)** Measured OCT-MCH preference versus preference predicted from PC 2 of PN activity in a training set (n=47 flies). **(D)** Measured OCT-MCH preference versus preference predicted from PC 2 on PN activity in a test set (n=22 flies) evaluated on a model trained on data from panel (C).

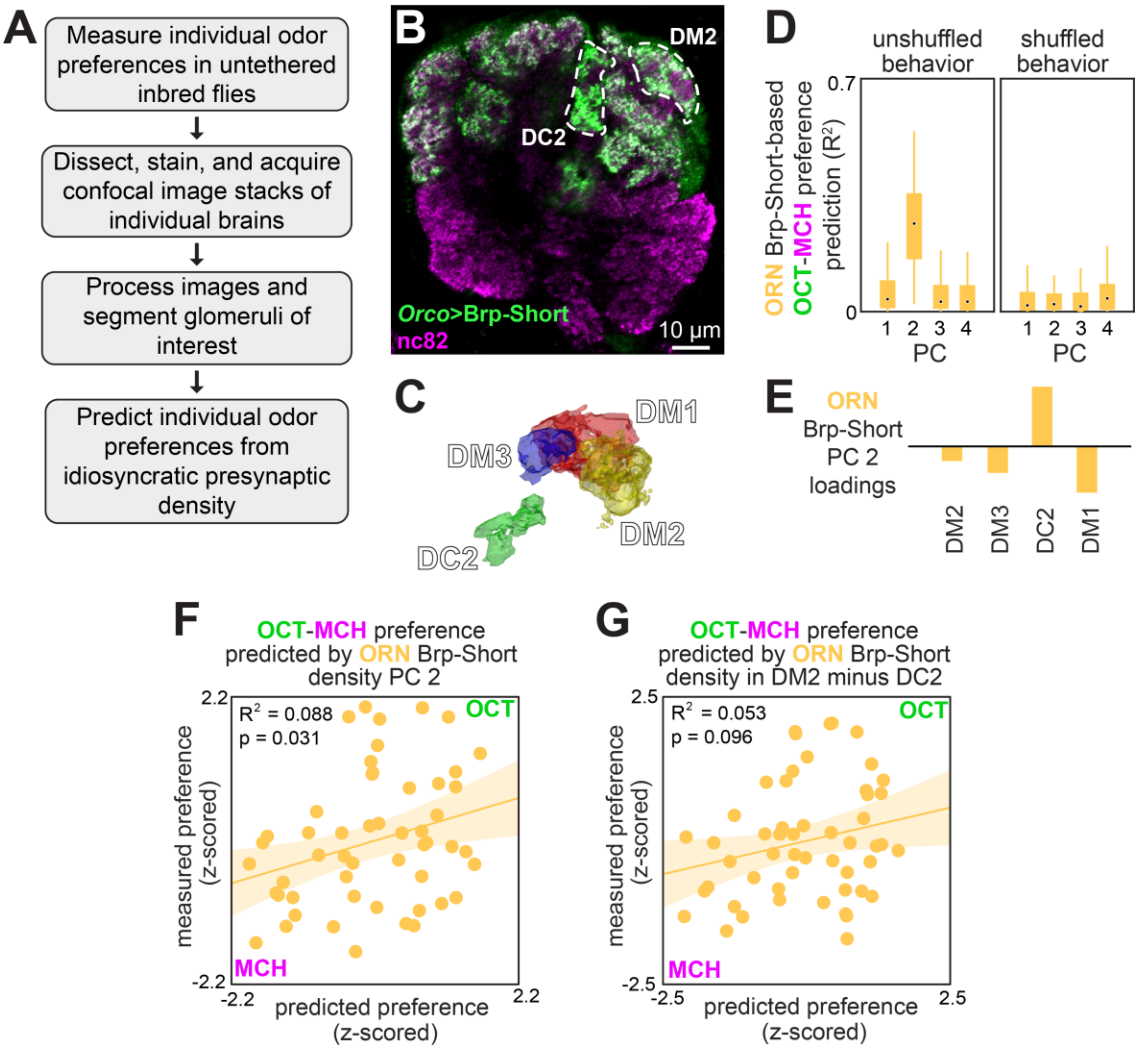


Figure 3. Idiosyncratic presynaptic marker density in DM2 and DC2 predicts OCT-MCH preference.

(A) Experiment outline. **(B)** Example slice from a z-stack of the antennal lobe expressing Orco>Brp-Short (green) with DC2 and DM2 visible (white dashed outline). nc82 counterstain (magenta). **(C)** Example glomerulus segmentation masks extracted from an individual z-stack. **(D)** Bootstrapped R^2 of OCT-MCH preference prediction from each of the first 4 principal components of Brp-Short density measured in ORNs (training set, n=22 flies). **(E)** PC 2 loadings of Brp-Short density. **(F)** Measured OCT-MCH preference versus preference predicted from PC 2 of ORN Brp-Short density in n=53 flies using a model trained on a training set of n=22 flies (see Figure 3 – figure supplement 1 for train/test flies analyzed separately). **(G)** Measured OCT-MCH preference versus preference predicted from ORN Brp-Short density in DM2 minus DC2 (n=53 flies).

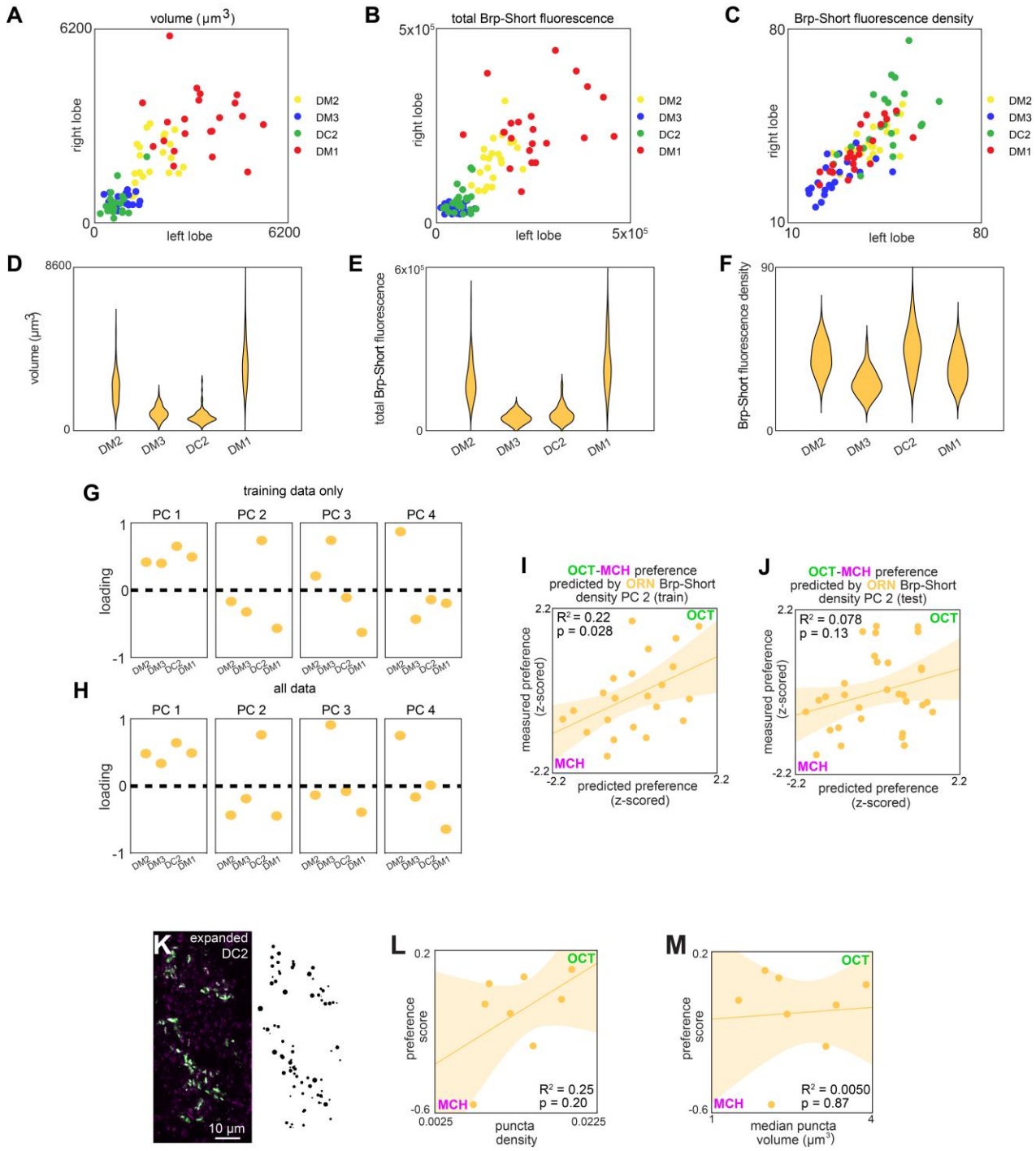


Figure 3 – figure supplement 1. ORN>Brp-Short characterization and model predictions. **(A-C)** Right versus left glomerulus properties measured from z-stacks of stained Orco>Brp-Short samples: (A) Volume, (B) total Brp-Short fluorescence, (C) Brp-Short fluorescence density. **(D-F)** Same data as panels (A-C) represented in violin plots (kernel density estimated). **(G)** Principal component loadings of Brp-Short density calculated using only training data (n=22 flies). **(H)** Principal component loadings of Brp-Short density calculated using all data (n=53 flies). **(I)** Measured OCT-MCH preference versus preference predicted from PC 2 of ORN Brp-Short density in a training set (n=22 flies). **(J)** Measured OCT-MCH preference versus

preference predicted from PC 2 on ORN Brp-Short density in a test set (n=31 flies) evaluated on a model trained on data from panel (I). **(K)** Example expanded AL expressing Or13a>Brp-Short (left) and Imaris-identified puncta from that sample (right). **(L)** OCT-MCH preference score plotted against Brp-Short puncta density in expanded Or13a>Brp-Short samples (n=8 flies). **(M)** OCT-MCH preference score plotted against Brp-Short median puncta volume in expanded Or13a>Brp-Short samples (n=8 flies). Shaded regions in F,G,I,J are the 95% CI of the fit estimated by bootstrapping.

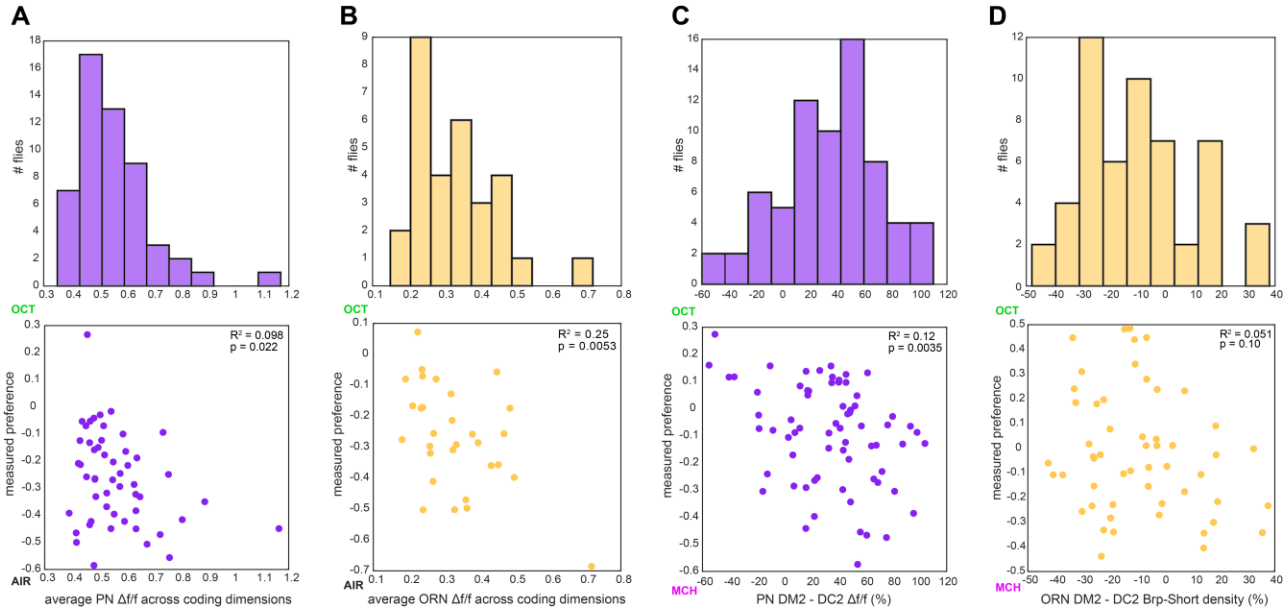
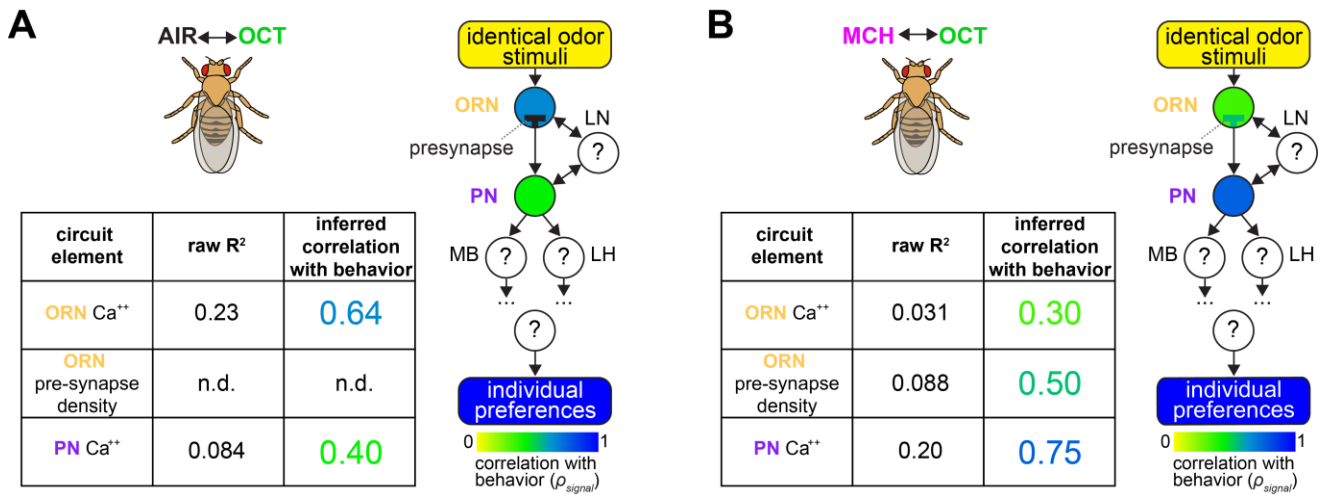


Figure 3 – figure supplement 2. Calcium and Brp-Short predictor variation.
(A) Histogram of average PN Δf/f across all coding dimensions in flies in which OCT-AIR preference was measured (top) and OCT-AIR preference versus average PN Δf/f (n=53 flies) (bottom). **(B)** Similar to (A) for ORN Δf/f and OCT-AIR preference (n=30 flies). **(C)** Similar to (A) for Δf/f difference between DM2 and DC2 PN responses and OCT-MCH preference (n=69 flies). **(D)** Similar to (A) for % Brp-Short density difference between DM2 and DC2 ORNs and OCT-MCH (n=53 flies).



circuit element	raw R^2	inferred correlation with behavior
ORN Ca^{++}	0.23	0.64
ORN pre-synapse density	n.d.	n.d.
PN Ca^{++}	0.084	0.40

circuit element	raw R^2	inferred correlation with behavior
ORN Ca^{++}	0.031	0.30
ORN pre-synapse density	0.088	0.50
PN Ca^{++}	0.20	0.75

Figure 4. Loci of individuality across the olfactory periphery.
(A) Table summarizing circuit element predictors, the strength of their nominal correlation with odor-vs-air behavior scores, and the inferred correlation between latent calcium / latent behavior. See analysis in Figure 4 – figure supplement 1. Schematic at right places these values in the context of the olfactory circuit. ORN Ca++ corresponds to PC 1 of ORN calcium (Figure 1L), PN Ca++ corresponds to PC1 of PN calcium (Figure 1M; trained model applied to train+test data). **(B)** As in (A) but for odor-vs-odor experiments. ORN Ca++ corresponds to PC 1 of ORN calcium (Figure 1O), ORN pre-synapse density corresponds to PC2 of Brp-Short relative fluorescence (Figure 3F; trained model applied to train+test data), PN Ca++ corresponds to PC 2 of PN calcium (Figure 1P; trained model applied to train+test data).

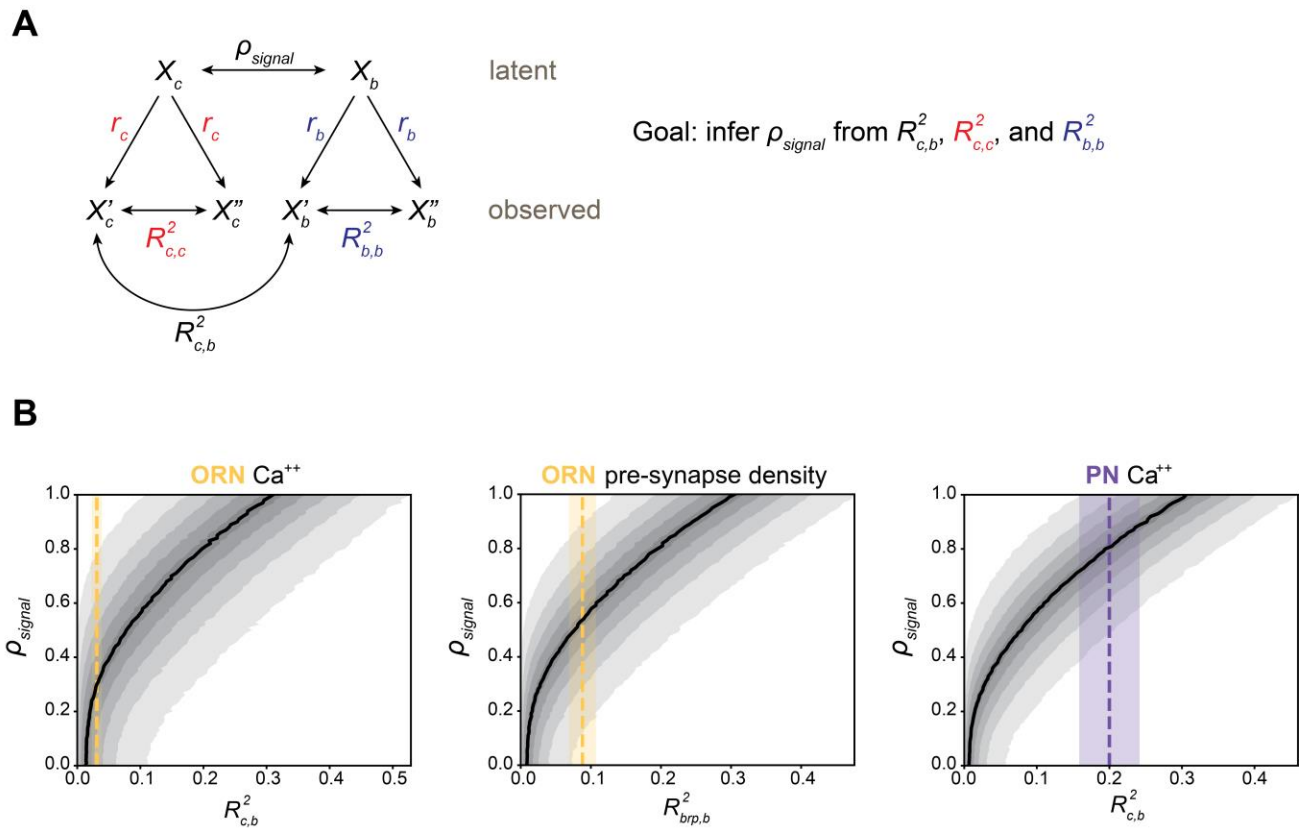


Figure 4 – figure supplement 1. Estimating latent calcium - behavior correlations.
(A) Schematic of inference approach to estimate the correlation between latent calcium (c) and behavioral (b) states (ρ_{signal}). This method can be applied identically to infer ρ_{signal} between Brp measurements and behavior. **(B)** Demonstration of ρ_{signal} inference for OCT vs MCH models presented in Figure 4: ORN calcium PC 1 (left, N=30, R^2=0.25 indicated in dashed line), ORN Brp-Short PC 2 from trained model applied to train+test data (middle, N=53, R^2=0.088 indicated in dashed line), PN calcium PC 2 from trained model applied to train+test data (right, N=69, R^2=0.20). Black line indicates median $R_{c,b}^2$ ($R_{brp,b}^2$ for Brp-Short model) among the 10,000 simulations for each ρ_{signal}, shaded areas (from lightest to darkest to lightest) indicate 5-15th, 15-25th, …, 85-95th percentile $R_{c,b}^2$ ($R_{brp,b}^2$). The marginal distribution for ρ_{signal} was estimated as the distribution of simulations for each ρ_{signal} for which the simulated $R_{c,b}^2$ ($R_{brp,b}^2$) had a value +/- 20% of the linear models' R^2 (dashed lines). For the examples depicted here, the median ρ_{signal} for ORN calcium PC1 was 0.30 (90% CI as estimated by the 5th-95th percentiles of the marginal distribution: 0.02-0.74), for ORN Brp-Short PC 2: 0.50 (0.11-0.85), for PN PC 2: 0.75 (0.44-0.96).

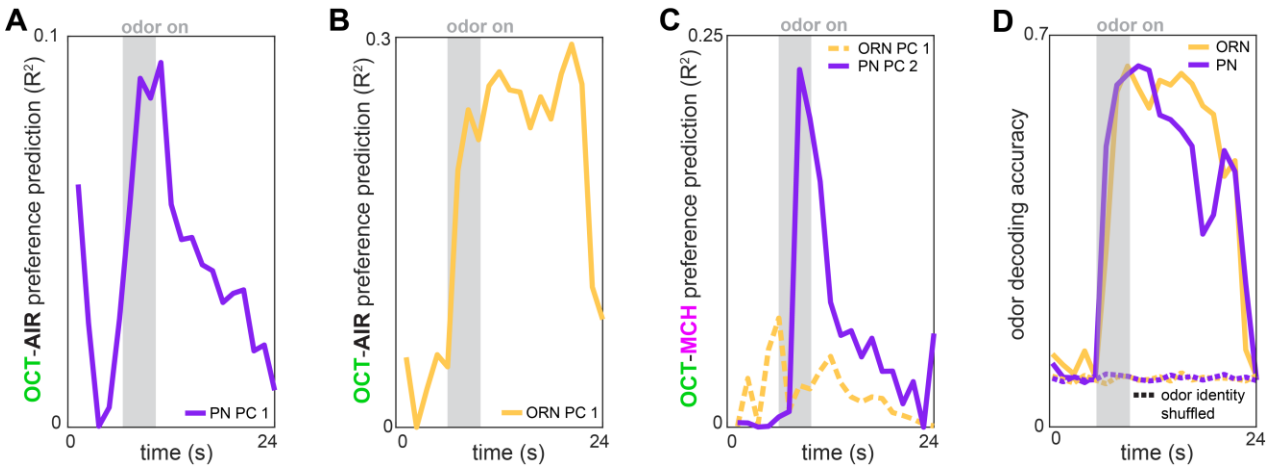


Figure 4 – figure supplement 2. Time-dependent preference- and odor-decoding.
(A) R^2 of odor-vs-air preference predicted by PC 1 of PN activity as a function of time across trials (n=53 flies). **(B)** R^2 of odor-vs-air preference predicted by PC 1 of ORN activity as a function of time across trials (n=30 flies). **(C)** R^2 of odor-vs-odor preference predicted by PC 2 of PN activity (solid plum, n=69 flies) or PC 1 of ORN activity (dashed peach, n=35 flies) as a function of time across trials. **(D)** Logistic regression classifier accuracy of decoding odor identity from 5 glomerular responses as a function of time. Dashed curves indicate performance on shuffled data.

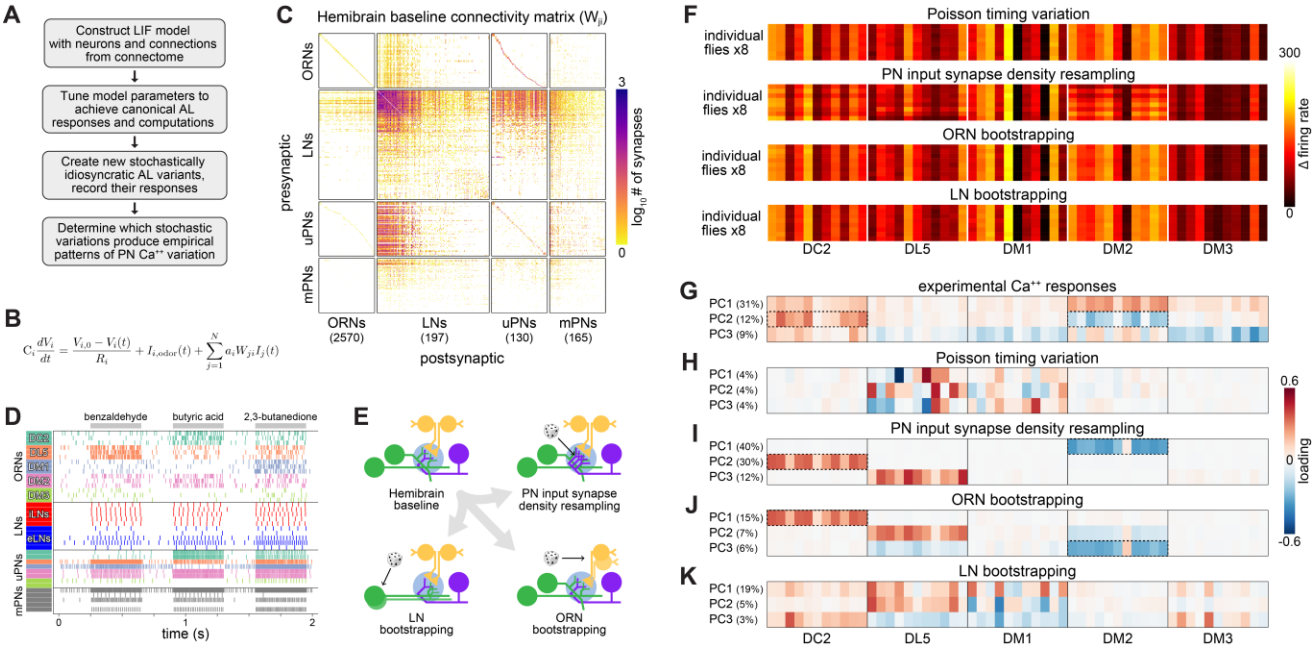


Figure 5. Simulation of developmentally stochastic olfactory circuits

(A) AL modeling analysis outline. **(B)** Leaky-integrator dynamics of each simulated neuron. When a neuron's voltage reaches its firing threshold, a templated action potential is inserted, and downstream neurons receive a postsynaptic current. See *Antennal Lobe modeling* in Materials and Methods. **(C)** Synaptic weight connectivity matrix, derived from the hemibrain connectome (Scheffer et al., 2020). **(D)** Spike raster for randomly selected example neurons from each AL cell type. Colors indicate ORN/PN glomerular identity and LN polarity (i=inhibitory, e=excitatory). **(E)** Schematic illustrating sources of developmental stochasticity as implemented in the simulated AL framework. See Supplementary Video 4 for the effects of these resampling methods on the synaptic weight connectivity matrix. **(F)** PN glomerulus-odor response vectors for 8 idiosyncratic ALs subject to Input spike Poisson timing variation, PN input synapse density resampling, and ORN and LN population bootstrapping. **(G)** Loadings of the principal components of PN glomerulus-odor responses as observed across experimental flies (top). Dotted outlines highlight loadings selective for the DC2 and DM2 glomerular responses, which underlie predictions of individual behavioral preference. **(H-K)** As in (G) for simulated PN glomerulus-odor responses subject to Input spike Poisson timing variation, PN input synapse density resampling, and ORN and LN population bootstrapping. See Figure 5 – figure supplement 5 for additional combinations of idiosyncrasy methods. In (F-K) the sequence of odors within each glomerular block is: OCT, 1-hexanol, ethyl-lactate, 2-heptanone, 1-pentanol, ethanol, geranyl acetate, hexyl acetate, MCH, pentyl acetate and butanol.

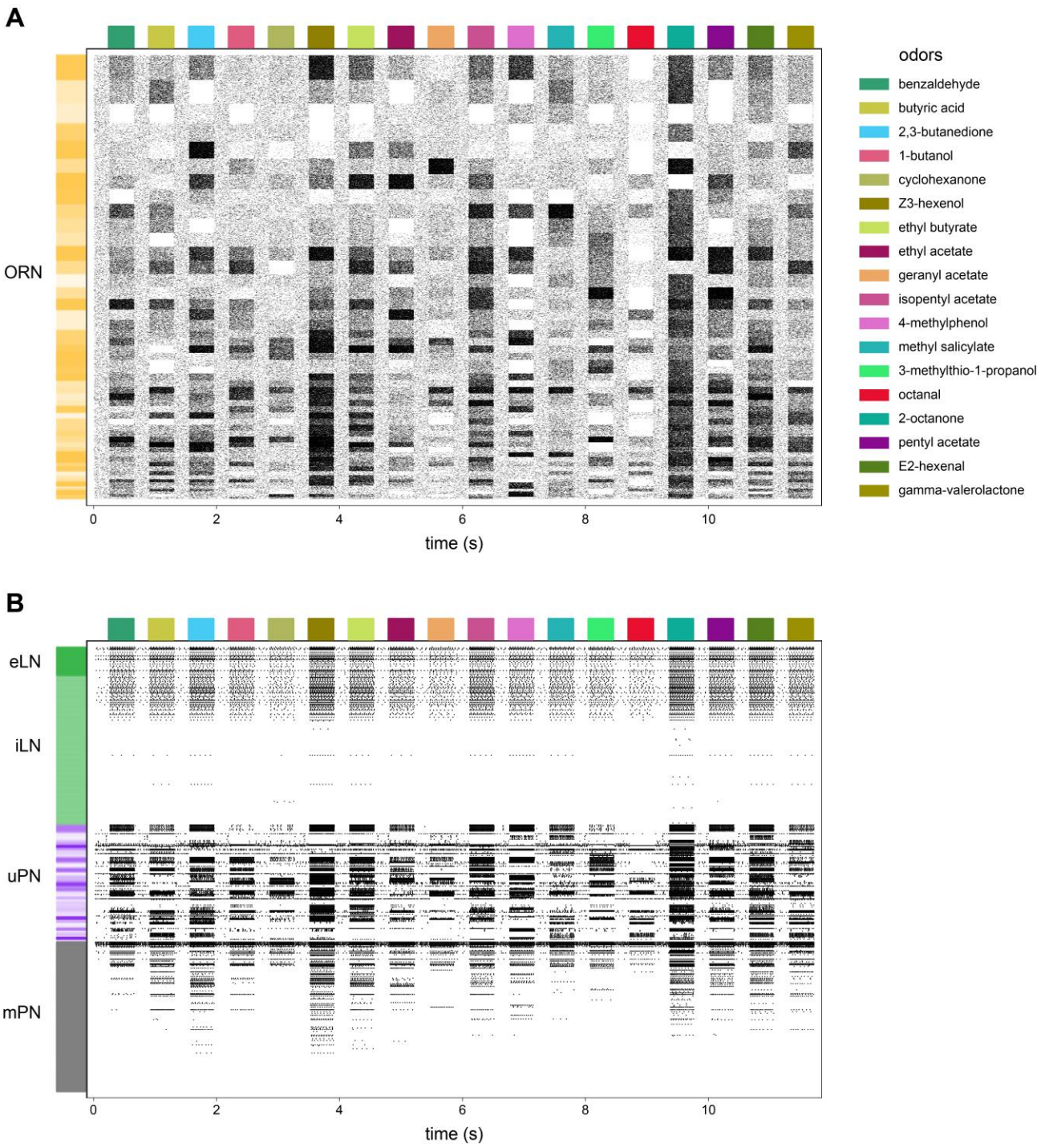


Figure 5 – figure supplement 1. AL model raster plot.

(A) Action potential raster plot of ORNs in the baseline simulated AL. Rows are individual ORNs, black ticks indicate action potentials. Random shades of orange at left indicate blocks of ORN rows projecting to the same glomerulus. **(B)** The remaining neurons in the model. Shades of green indicate excitatory vs inhibitory LNs and shades of purple indicate PNs with dendrites in the same glomeruli.

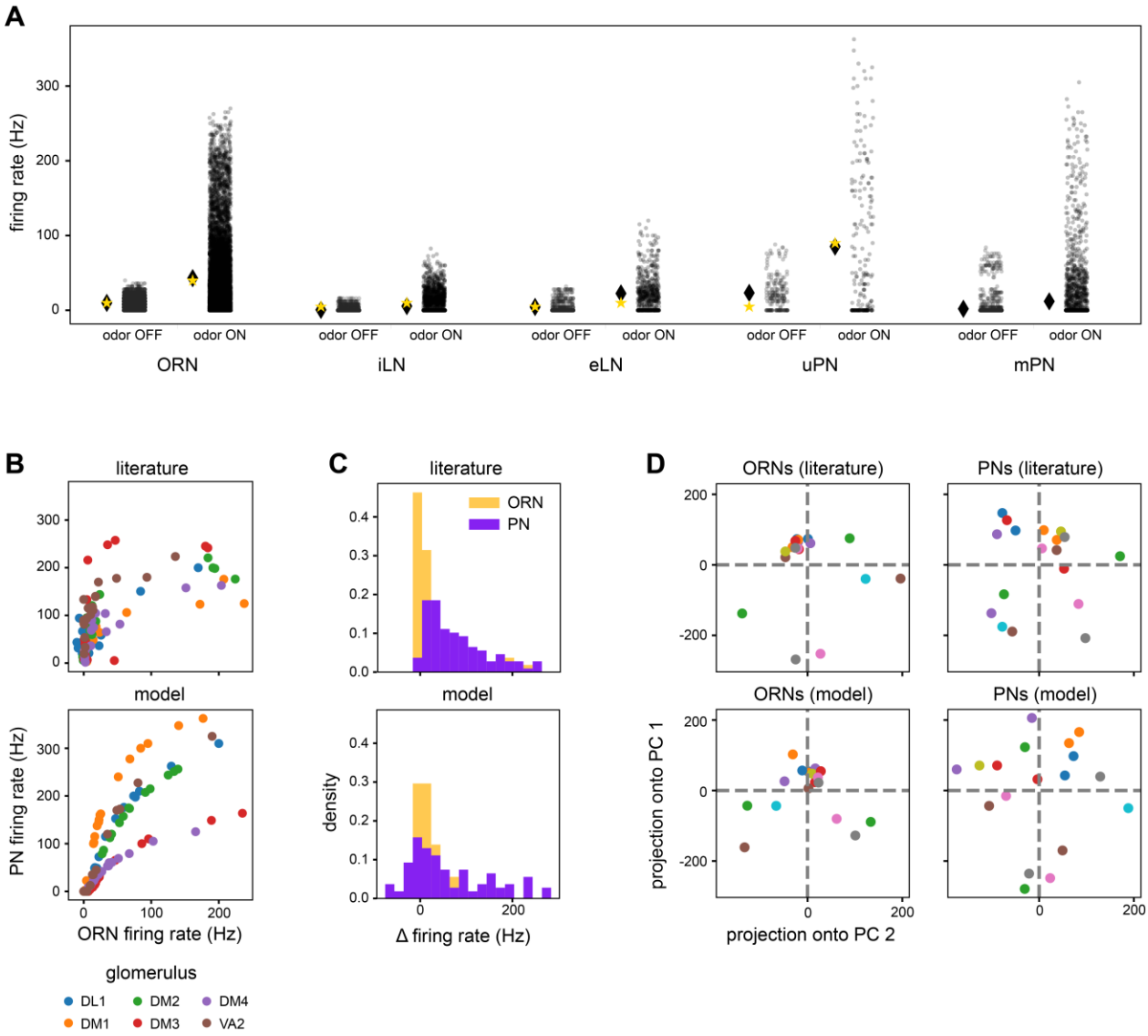


Figure 5 – figure supplement 2. AL model baseline outputs compared to experimental data. **(A)** Distributions of model neuron firing rates by cell type across odors (transparent black points are individual neuron-odor combinations). Black lozenge symbols indicate the mean firing rate of the points to the right. Yellow stars indicate the comparable experimental values reported in (Chou et al., 2010; de Bruyne et al., 2001; Nagel et al., 2015; Wilson, 2004). **(B)** Scatter plots of average PN firing rate vs ORN firing rate during odor stimuli in the model vs experimental values (Bhandawat et al., 2007). Points are odors, colors are glomeruli. **(C)** Histograms of ON odor minus OFF odor glomerulus-average PN and ORN firing rates in the model vs experimental values (Bhandawat et al., 2007), showing flatter distributions in PNs. **(D)** Odor representations in the first 2 PCs of glomerulus-average ORN responses and PN responses in the model and experimental results (Bhandawat et al., 2007). Points are odors. Pairwise distances between PN representations are more uniform than in ORNs in both the model and experimental data. Panels (B)-(D) use glomerulus-average PN and ORN firing rates from six of the seven glomeruli in Bhandawat et al., 2007, as VM2 is significantly truncated in the hemibrain (Scheffer et al., 2020). Literature features in panels (B)-(D) were extracted from Bhandawat et al., 2007 using WebPlotDigitizer (Rohatgi, 2021).

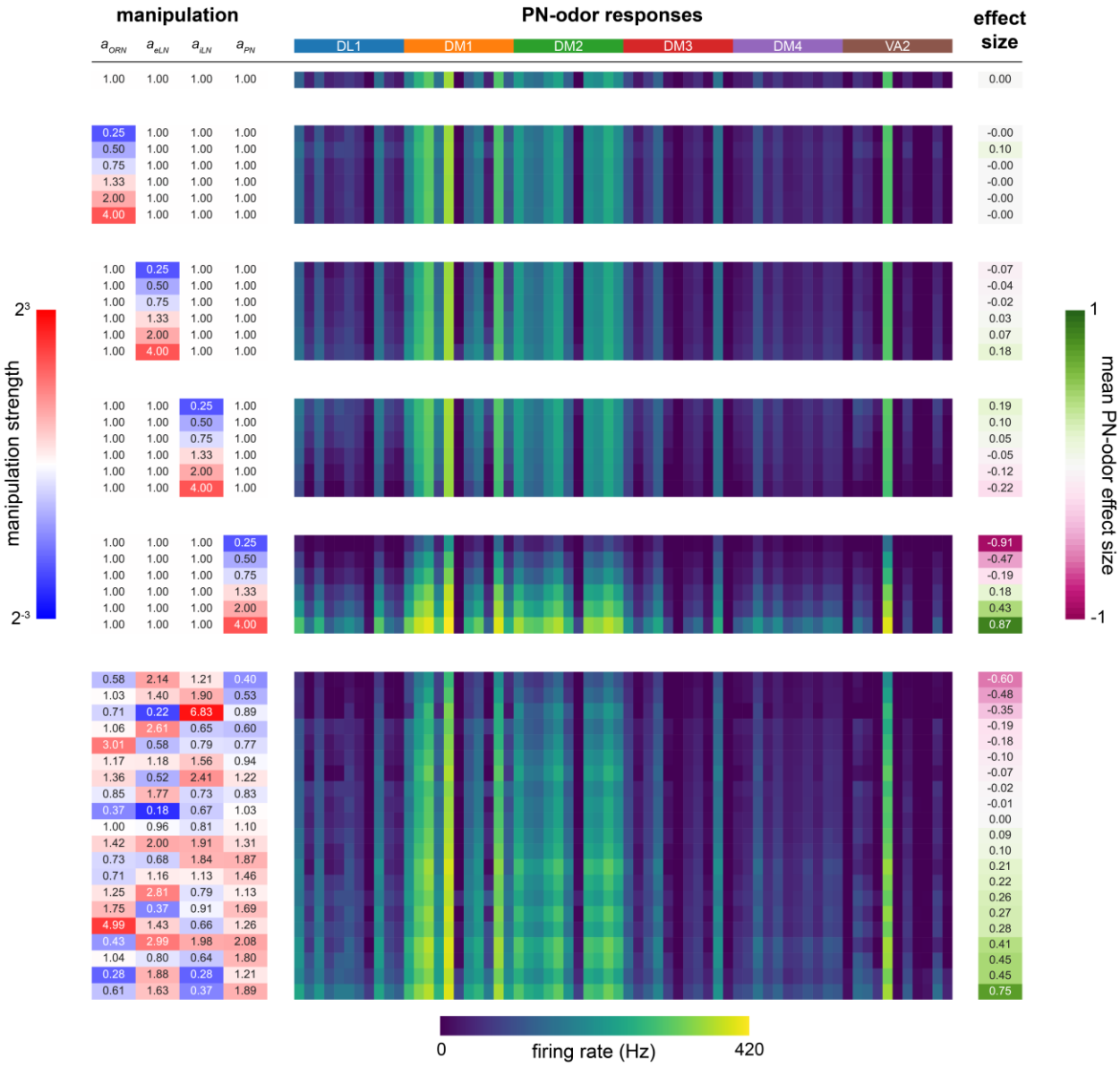


Figure 5 – figure supplement 3. Sensitivity analysis of a_{ORN}, a_{eLN}, a_{iLN}, a_{PN} parameters. (Left, blue to red colormap): magnitude of parameter manipulation. (Center, dark blue to yellow colormap): mean glomerular firing rate (Hz) responses of PNs (DL1, DM1, DM2, DM3, DM4, VA2) to 11 odors (order within each glomerulus (colored bands at top): 3-octanol, 1-hexanol, ethyl lactate, 2-heptanone, 1-pentanol, ethanol, geranyl acetate, hexyl acetate, 4-methylcyclohexanol, pentyl acetate, 1-butanol, 3-octanol). (Right, pink to green colormap): manipulation effect size on mean PN-odor responses (Cohen's *d*). (Top): baseline parameter set. (Middle): single-parameter manipulations from 1/4x to 4x. (Bottom): multiple-parameter manipulations. For further detail see *AL model tuning* in Materials and Methods. No manipulations yielded effect sizes larger than 0.9; a_{PN} is the most sensitive parameter.

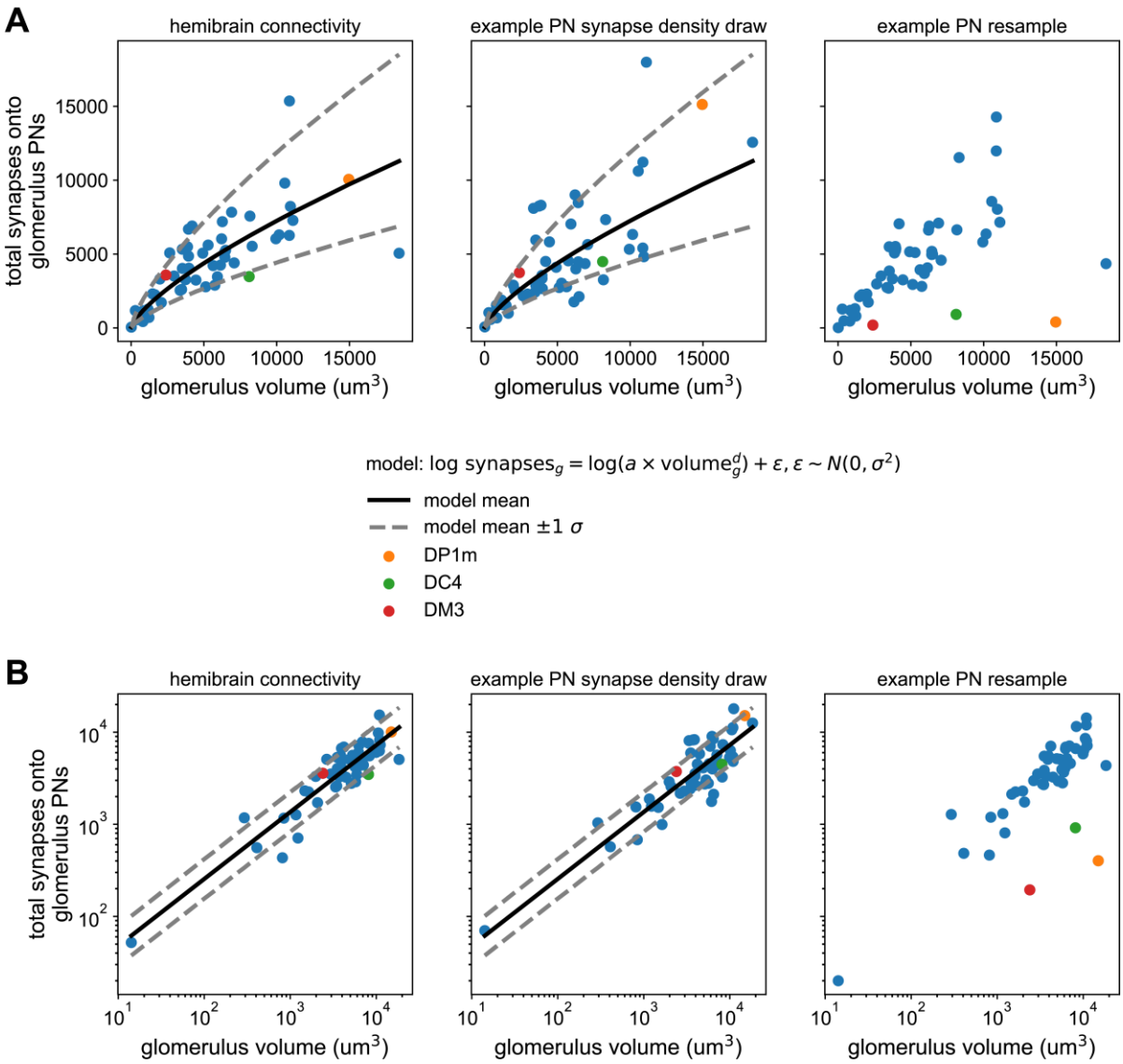


Figure 5 – figure supplement 4. Synapse counts vs glomerular volume in the hemibrain and AL model.

(A) Left) Scatter plot of total PN input synapses within a glomerulus vs that glomerulus' volume from the hemibrain data set. Solid line represents the maximum likelihood-fit mean synapse count vs glomerular volume, and dashed lines the fit +/-1 standard deviation. Middle) As (left) but for a single sample from the parameterized distribution of PN input synapses vs glomerular volume. Right) As in previous for a single bootstrap resample of PNs. Color-highlighted glomeruli illustrate that when PNs within a glomerulus have highly asymmetrical synapse counts, bootstrapping them alone can result in apparent synapse densities that lie outside the empirical distribution (left). **(B)** As in (A) but on log-log axes, showing the linear relationship between synapse density and glomerular volume after this transformation, and bootstrapped densities falling outside this distribution at right.

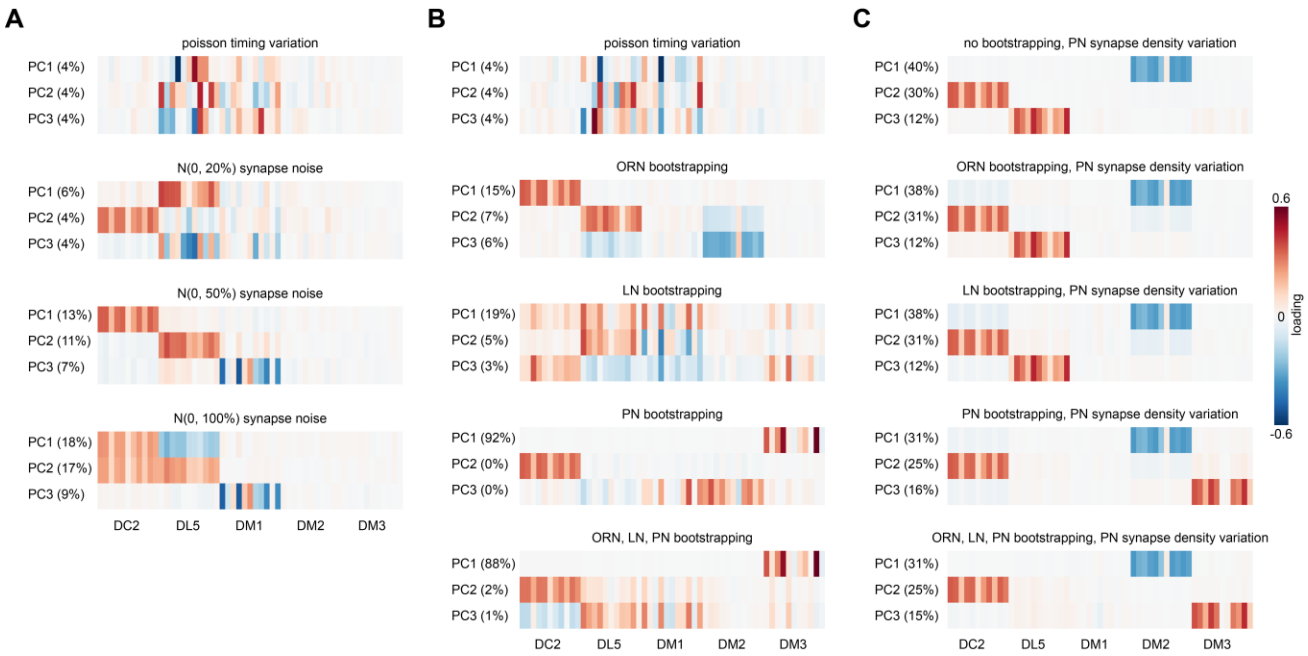


Figure 5 – figure supplement 5. PN response PCA loadings under various sources of circuit idiosyncrasy.

(A) Loadings of the principal components of PN glomerulus-odor responses as simulated across AL models where Gaussian noise with a standard deviation equal to 0, 20, 50, and 100% of each synapse weight was added to each synaptic weight in the hemibrain data set. **(B)** circuit variation coming from bootstrapping of each major AL cell type or all three simultaneously. **(C)** circuit variation coming from bootstrap resampling of different cell-type combinations in addition to PN input synapse density resampling as illustrated in Figure 5 – figure supplement 4.

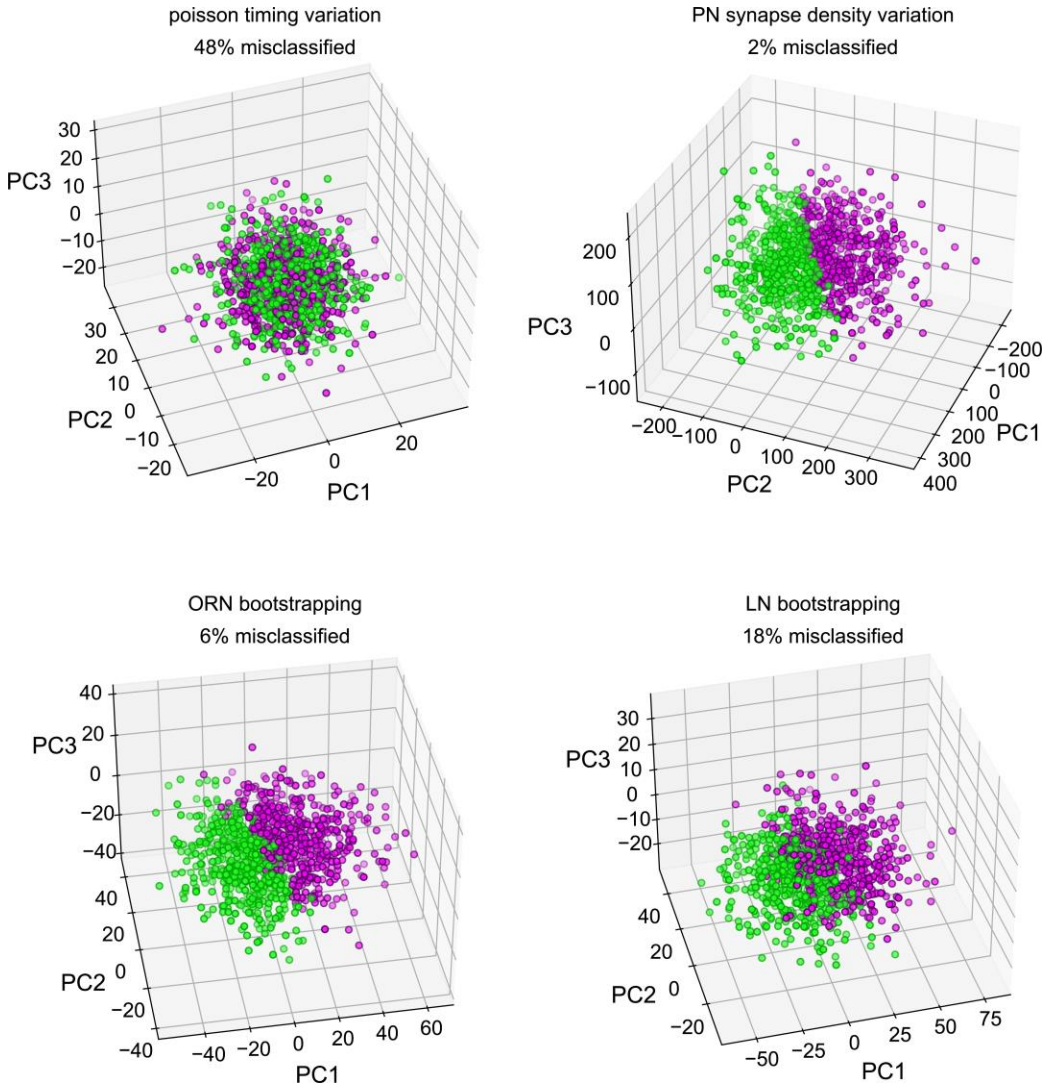


Figure 5 – figure supplement 6. Classifiability of simulated idiosyncratic behavior under different sources of circuit idiosyncrasy.

Simulated PN odor-glomerulus firing rates projected into their first 3 principal components. Individual points represent single runs of resampled AL models, under four different sources of idiosyncratic variation. PN responses in all odor-glomerulus dimensions were used to calculate simulated behavior scores for each resampled AL, by applying the PN calcium-odor-vs-odor linear model (Figure 2G). Magenta points represent flies with simulated preference for MCH in the top 50%, and green OCT preference. % Misclassification refers to 100% – the accuracy of a linear classifier trained on MCH-vs-OCT preference in the space of the first three PCs. This measures how much of the variance along the PN calcium-odor-vs-odor linear model lies outside the first three PCs of simulated PN variation.

Tables

Table 1: Calcium & Brp-Short – behavior model statistics

Behavior Measured	Neural Predictor	Figure Panel	n	β_0	β_1	R^2	p-value
OCT vs. AIR	PN Calcium PC 1 (Figure 2A)	Figure 2 – figure supplement 1A	18	-0.26	-0.079	0.16	0.099
OCT vs. AIR	PN Calcium Average all dimensions	2C	53	-0.051	-0.38	0.098	0.022
OCT vs. AIR	ORN Calcium PC 1 (Figure 2D)	1L	30	-0.29	-0.053	0.23	0.007
OCT vs. AIR	ORN Calcium Average all dimensions	2F	30	-0.032	-0.71	0.25	0.005
OCT vs. MCH	PN Calcium PC 2 (Figure 2G)	Figure 2 – figure supplement 1C	47	-0.058	-0.081	0.15	0.006
OCT vs. MCH	PN Calcium DM2 - DC2 (% difference)	2I	69	-0.032	-0.0018	0.12	0.004
OCT vs. MCH	ORN Calcium PC 1	1O	35	-0.14	-0.027	0.031	0.32
OCT vs. MCH	ORN Brp-Short PC 2 (train data only) (Figure 3E)	Figure 3 – figure supplement 1I	22	-0.087	0.017	0.22	0.028
OCT vs. MCH	ORN Brp-Short PC 2 (all data)	3F	53	-0.019	0.012	0.088	0.031
OCT vs. MCH	ORN Brp-Short DM2 - DC2	3G	53	-0.051	-0.007	0.053	0.096

1476 **Table 2: Typical electrophysiology features of AL cell types, used as model parameters**

Parameter	ORNs	LNs	PNs
Membrane resting potential	-70 mV (Dubin and Harris, 1997)	-50 mV (Seki et al., 2010)	-55 mV (Jeanne and Wilson, 2015)
Action potential threshold	-50 mV (Dubin and Harris, 1997)	-40 mV (Seki et al., 2010)	-40 mV (Jeanne and Wilson, 2015)
Action potential minimum	-70 mV (Cao et al., 2016)	-60 mV (Seki et al., 2010)	-55 mV (Jeanne and Wilson, 2015)
Action potential maximum	0 mV (Dubin and Harris, 1997)	0 mV (Seki et al., 2010)	-30 mV (Wilson and Laurent, 2005)
Action potential duration	2 ms (Jeanne and Wilson, 2015)	4 ms (Seki et al., 2010)	2 ms (Jeanne and Wilson, 2015)
Membrane capacitance	73 pF (assumed = PNs)	64 pF (Huang et al., 2018)	73 pF (Huang et al., 2018)
Membrane resistance	1.8 GOhm (Dubin and Harris, 1997)	1 GOhm (Seki et al., 2010)	0.3 GOhm (Jeanne and Wilson, 2015)

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Supplementary Videos

Supplementary Video 1. Example recording with automated tracking of an odor-vs-air behavioral assay.
The recent positions of each fly (green line) are shown in different colors. Red bar indicates when the odor stream is turned on.

Supplementary Video 2. Example recording with automated tracking of an odor-vs-odor behavioral assay.
The recent positions of each fly (green line) are shown in different colors. Magenta and green bars at right indicate when MCH and OCT are respectively flowing into the top and bottom halves of each arena.

Supplementary Video 3. Confocal image stack of expanded DC2>Brp-Short.
Magenta is nc82 stain, Green is Or13a>Brp-Short. Frames are z-slices spaced at 0.54 µm. Image height corresponds to a post-expansion field of view of 107 x 90 µm (a ~2.5 x linear expansion factor).

Supplementary Video 4. Simulated AL connectivity matrices.
Left: Glomerular density resampling. Each frame corresponds to the hemibrain connectome synaptic weights, rescaled according to a sample from the relationship between synapse count and volume parameterized in Figure 5 – figure supplement 4. Middle: ORN bootstrapping. Each frame corresponds to the hemibrain connectome synaptic weights, but with the population of ORNs projecting to each glomerulus resampled with replacement. Right: LN bootstrapping. Each frame corresponds to the hemibrain connectome synaptic weights, but with the population of LNs resampled with replacement.