

1 **Title:** Odor imagery but not perception drives risk for food cue reactivity and increased adiposity

2

3 **Authors:** Emily E. Perszyk^{a,b,*}, Xue S. Davis^{a,b}, Jelena Djordjevic^d, Marilyn Jones-Gotman^d,
4 Jessica Trinh^{a,b}, Zach Hutelin^{a,b}, Maria G. Veldhuizen^e, Leonie Koban^f, Tor D. Wager^g, Hedy
5 Kober^{b,c}, Dana M. Small^{a,b,c,*}

6

7 **Affiliations:**

8 ^a Modern Diet and Physiology Research Center, New Haven, CT 06510, USA

9 ^b Department of Psychiatry, Yale University School of Medicine, New Haven, CT 06511, USA

10 ^c Department of Psychology, Yale University, New Haven, CT 06511, USA

11 ^d Department of Neurology and Neurosurgery, Montreal Neurological Institute and Hospital,
12 McGill University, Montréal, QC H3A 2B4, Canada

13 ^e Department of Anatomy, Faculty of Medicine, Mersin University, Ciftlikkoy Campus, Mersin
14 33343, Turkey

15 ^f Lyon Neuroscience Research Center (CRNL), CNRS, INSERM, University Claude Bernard
16 Lyon 1, France

17 ^g Department of Psychological and Brain Sciences, Dartmouth College, Hanover, NH 03755,
18 USA

19

20 ***Correspondence:** emily.perszyk@yale.edu or dana.small@yale.edu

21 **ABSTRACT**

22 Mental imagery has been proposed to play a critical role in the amplification of cravings.
23 Here we tested whether olfactory imagery drives food cue reactivity strength to promote
24 adiposity in 45 healthy individuals. We measured odor perception, odor imagery ability, and food
25 cue reactivity using self-report, perceptual testing, and neuroimaging. Adiposity was assessed
26 at baseline and one year later. Brain responses to real and imagined odors were analyzed with
27 univariate and multivariate decoding methods to identify pattern-based olfactory codes. We
28 found that the accuracy of decoding imagined, but not real, odor quality correlated with a
29 perceptual measure of odor imagery ability and with greater adiposity changes. This latter
30 relationship was mediated by cue-potentiated craving and intake. Collectively, these findings
31 establish odor imagery ability as a risk factor for weight gain and more specifically as a
32 mechanism by which exposure to food cues promotes craving and overeating.

33

34 **Keywords:** olfaction, imagery, food cue reactivity, craving, food intake, fMRI, obesity, piriform
35 cortex, neuroimaging

36 INTRODUCTION

37 The 21st century rise in obesity coincides with the increased prevalence of palatable,
38 energy-dense foods and ubiquitous cues signaling their availability¹. Conditioned responses to
39 food cues, such as increased salivation and brain responses, provide a measure of food cue
40 reactivity. According to the 'cued overeating model,' such physiological and neural changes may
41 be consciously experienced as craving, an intense desire for a particular food^{2,3}. Food cue
42 reactivity is positively associated with body mass index (BMI)⁴ and highly predictive of weight
43 change⁵.

44 One prominent theory of craving posits that repeated mental imagery of the sensory
45 properties of a desired substance (e.g., food) leads to the intensification of cravings⁶.
46 Specifically, the Elaborated Intrusion Theory of Desire argues that craving episodes persist in a
47 vicious cycle by which mental images provide immediate pleasure but exacerbate the
48 awareness of a deficit and promote further planning to satisfy the desire⁶. Sensory imagery is a
49 primary component of subjective food, drug, and alcohol craving, and the self-reported vividness
50 of this mental imagery is positively associated with craving strength⁷⁻¹³. Accordingly, protocols in
51 which individuals are asked to imagine palatable foods are frequently used to induce craving¹⁴.

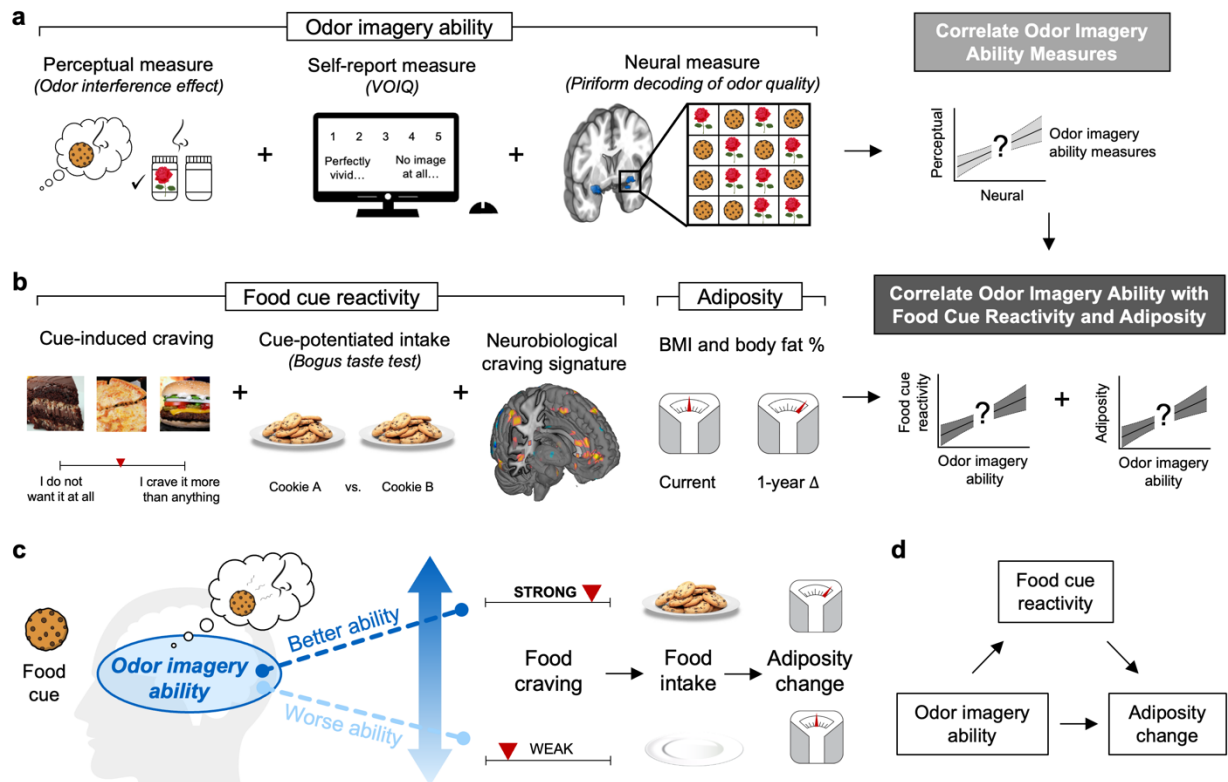
52 Of central relevance to the current investigation, not all sensory modalities are similarly
53 imaginable. The self-reported ability to imagine sights and sounds is nearly universal, whereas
54 the ability to imagine odors and flavors varies widely across the population¹⁵⁻¹⁹. Previous work
55 from our lab demonstrated that the self-reported vividness of imagined olfactory, but not visual,
56 stimuli positively correlates with BMI²⁰. These data raise the possibility that odor imagery ability
57 confers risk for food cue reactivity and weight gain; however, whether this self-report measure
58 reflects actual odor imagery ability is not clear. Also unknown is whether perceptual or neural
59 measures of odor imagery ability are related to food cue reactivity, BMI, and weight gain
60 susceptibility.

61 Odor imagery ability has been quantified as the extent to which imagining an odor
62 decreases the detectability of a weak incongruent odor²¹. This 'interference effect' correlates
63 with self-reported odor imagery ability in women²¹. It has also been used to identify good odor
64 imagers (i.e., people with strong interference effects) who exhibit odor-imagery evoked
65 increases in regional cerebral blood flow measured by positron emission tomography in primary
66 and secondary olfactory regions²². However, since these regions are functionally
67 heterogeneous²³, the correlation might reflect general processes like attention, saliency, and
68 pleasantness, or more specific processes like odor quality coding. This distinction is important
69 because imagery is based on the ability to reactivate sensory circuits that code the identity of

70 the imagined stimulus²⁴. In the case of olfaction, odor quality is encoded in patterns of activity
71 across piriform cortex neurons^{25–27}. In humans, these patterns can be decoded with multi-voxel
72 pattern analyses (MVPA) of functional magnetic resonance imaging (fMRI) data²⁸. Whether
73 imagining an odor reactivates these odor quality patterns has not been tested.

74 In the current study, we set out to first determine if the interference effect – a
75 performance-based perceptual measure of odor imagery ability – is associated with self-
76 reported ability and the decoding of odor quality from fMRI patterns evoked by real and/or
77 imagined odors in the piriform cortex (Fig. 1a). Our second goal was to test if the perceptual
78 (i.e., the interference effect) and neural (i.e., piriform decoding of imagined odors) measures of
79 odor imagery ability are associated with behavioral food cue reactivity, quantified as cue-
80 induced craving and cue-potentiated food intake (Fig. 1b). We also explored whether imagining
81 odors elicits an independently established brain measure of food cue reactivity (Fig. 1b), the
82 Neurobiological Craving Signature (NCS). The NCS is a recently developed multivariate brain
83 activity pattern, or neuromarker, that predicts the intensity of self-reported food and drug craving
84 across distinct samples²⁹. Finally, we sought to test if odor imagery is associated with current or
85 change in adiposity over one year (Fig. 1b). We hypothesized that better odor imagery ability
86 would be associated with stronger food cue reactivity and greater change in adiposity (Fig. 1c),
87 with food cue reactivity mediating the association between odor imagery and adiposity change
88 (Fig. 1d).

89



90

91

Fig. 1: Study Overview and Model

92

(a) Our first goal was to establish relationships between three measures of odor imagery ability: a validated perceptual measure adapted from Djordjevic et al. (2004)²¹, a self-report measure (the Vividness of Olfactory Imagery Questionnaire or VOIQ³⁰), and a new neural measure based upon the piriform decoding of odor quality. See Figs. 2–4 for additional details on the perceptual and neural measures.

96

(b) Our second goal was to correlate odor imagery ability with two behavioral measures of food cue reactivity: cue-induced craving from an established paradigm³¹ and cue-potentiated intake in a bogus taste test³². We also examined the extent to which smelling versus imagining odors elicits an independently established brain measure of food cue reactivity, the Neurobiological Craving Signature²⁹. Our third goal was to test the associations between odor imagery ability and both current and one-year changes in adiposity.

101

(c) We hypothesized that in response to learned food cues, individuals with a better ability to imagine odors would experience stronger cravings that compel them to overeat and gain weight. In contrast, individuals with a worse ability to imagine odors would experience weaker cravings that have a low impact on their eating and weight.

104

(d) We predicted that food cue reactivity would mediate the association between odor imagery ability and adiposity change, such that odor imagery indirectly affects adiposity change via a food cue reactivity-dependent mechanism.

106

107

To test these hypotheses, we collected data from 45 adults (ages 18 – 42 years) with a range of BMIs (18.32 – 53.44 kg/m²). Participants completed three behavioral sessions and an fMRI scan at baseline to quantify odor imagery ability and food cue reactivity. They returned one year later for a follow-up session to assess adiposity change. As predicted, stronger

110

111 interference effects were associated with better decoding accuracies of imagined, but not real,
112 odors in the piriform cortex. Decoding also correlated positively with food intake. Most
113 importantly, food craving and intake mediated the relationships between odor imagery ability
114 and changes in BMI and body fat percentage, respectively. Collectively, these findings establish
115 odor imagery ability as a risk factor for weight gain susceptibility and more specifically as a
116 mechanism by which exposure to food cues promotes food craving and subsequent intake.

117

118 **RESULTS**

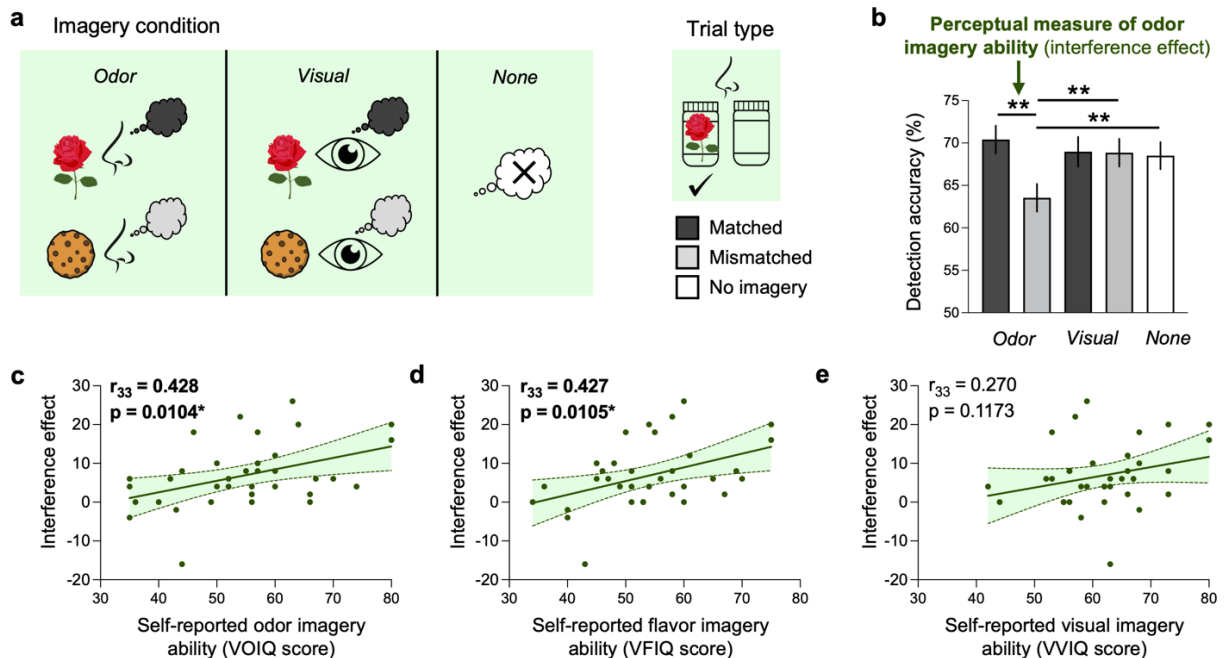
119 **Self-Report and Perceptual Measures of Odor Imagery Ability are Correlated**

120 To assess subjective experience of the ability to imagine odors and flavors, we used the
121 Vividness of Olfactory Imagery Questionnaire (VOIQ)³⁰ and the Vividness of Food Imagery
122 Questionnaire (VFIQ)²⁰, respectively. Our performance-based perceptual measure was adapted
123 from Djordjevic et al. (2004)²¹ and is detailed in the Materials and Methods section (and see Fig.
124 2a). In brief, participants were instructed to imagine the smell or sight of a rose or cookie while
125 trying to determine which of two samples contained either the same odor (matched trial) or the
126 other odor (mismatched trial) at their detection threshold level (determined prior to the test). In
127 the no imagery condition, odor detection trials were performed in the absence of imagery. The
128 interference effect (i.e., perceptual measure of odor imagery ability) was calculated by
129 subtracting detection accuracy (% trials correct) in mismatched trials from that in matched trials
130 of the odor imagery condition.

131 As in previous work²¹, we found a significant interaction between imagery condition
132 (odor/visual) and trial type (matched/mismatched) on detection accuracy after controlling for
133 odor type (rose/cookie; $F_{1,275} = 6.270$, $p = 0.0129$). This was driven by worse performance on
134 mismatched compared to matched trials during odor ($t_{137} = 3.870$, $p = 0.0002$), but not visual
135 ($t_{137} = 0.055$, $p = 0.9560$) imagery (Fig. 2b). We next tested whether facilitation during matched
136 trials, interference during mismatched trials, or a combination of the two contributed to this
137 effect. We observed no impact of imagery condition on detection accuracy in matched versus no
138 imagery trials ($F_{1,207} = 2.926$, $p = 0.0886$). In contrast, there was a main effect of imagery on
139 detection across mismatched and no imagery trials ($F_{1,207} = 6.187$, $p = 0.0137$). Follow-up
140 pairwise comparisons revealed that participants performed worse during odor mismatched
141 versus visual mismatched trials ($t_{137} = 2.712$, $p = 0.0076$) and during odor mismatched versus
142 no imagery trials ($t_{137} = 2.434$, $p = 0.0162$). There was no difference in visual mismatched
143 versus no imagery trials ($t_{137} = 0.163$, $p = 0.8709$). Collectively, these data replicate prior

144 findings showing that odor imagery impairs mismatched odor detection without improving
145 matched detection²¹.

146 To determine whether this perceptual measure corresponded to self-reported odor
147 imagery ability, we correlated the interference effect with perceived vividness of imagined odors
148 (VOIQ³⁰) and flavors (VFIQ²⁰). Both correlations were significant (Fig. 2c and 2d). By contrast,
149 no significant association was observed between the interference effect and self-reported visual
150 imagery (Fig. 2e) in the Vividness of Visual Imagery Questionnaire (VVIQ)¹⁷. Similarly, the
151 difference in detection accuracy on matched versus mismatched trials of the visual imagery
152 condition did not correlate with self-reported odor ($r_{33} = 0.306$, $p = 0.0735$), flavor ($r_{33} = 0.247$, p
153 $= 0.1519$), or visual ($r_{33} = 0.155$, $p = 0.3742$) imagery ability. The self-report and perceptual
154 measures of odor imagery ability also did not vary by sex, age, household income, olfactory
155 function, odor ratings, sniff parameters, hunger, or typical consumption of unhealthy foods
156 (Supplementary Tables 1 and 2). These results confirm that the self-report and perceptual
157 measures are associated, supporting the validity of using the interference effect as a measure
158 of odor imagery ability.



159

160 **Fig. 2: The Perceptual Measure of Odor Imagery Ability Correlates Positively with Self-Reported**
161 **Odor and Flavor, but not Visual, Imagery Ability**

162 (a) In the adapted perceptual task²¹ to quantify odor imagery ability, participants were instructed to imagine the smell or
163 sight of a rose/cookie or nothing at all while trying to detect either the same (matched trial) or the other (mismatched trial)
164 odor at their threshold level.

165 (b) An ANOVA revealed a significant imagery condition \times trial type interaction on detection accuracy. This effect was a
166 result of the interference (rather than facilitation) of odor imagery on detection, such that performance on mismatched
167 trials was significantly worse during odor imagery than in the visual or no imagery conditions.

168 (c–e) The perceptual measure of odor imagery ability (i.e., the interference effect) positively correlated with self-reported
169 odor (c) and flavor (d), but not visual (e), imagery ability.

170 Bar plots represent $M \pm SEM$. Fitted scatterplots depict single participants and the 95% CI. VOIQ, Vividness of Olfactory
171 Imagery Questionnaire³⁰; VFIQ, Vividness of Food Imagery Questionnaire²⁰; VVIQ, Vividness of Visual Imagery
172 Questionnaire¹⁷. * $p < 0.05$; **post-hoc comparison $p < 0.0167$ (0.05 / 3 tests).

173

174 **Imagining and Smelling Odors Activate Partly Overlapping Brain Regions**

175 To assess brain responses to real odors, rose and cookie odors (or clean air) were
176 repeatedly delivered via an olfactometer at moderate intensity to participants undergoing fMRI
177 scanning. These trials were interspersed with ones in which participants were instructed to
178 imagine the odors while sniffing clean air (Fig. 3a). As there was no main effect of odor type
179 (rose/cookie) on fMRI activity (all p_{FWE} [family-wise error corrected] ≥ 0.3214), we collapsed
180 across the odorants in the subsequent univariate analyses. Consistent with previous studies, we
181 observed a main effect of smelling odors $>$ smelling clean air in the bilateral insula,
182 piriform/amygdala, orbitofrontal cortices, cerebellum, and middle frontal and cingulate gyri,
183 along with the right thalamus and supramarginal gyrus and the left pre- and postcentral gyri
184 (Fig. 3b, Supplementary Table 3). Many of the same regions were responsive to imagining
185 odors $>$ imagining clean air, including the bilateral insula, right putamen, and left cerebellum
186 (Fig. 3c, Table 1). Given that most prior neuroimaging studies on odor imagery have contrasted
187 imagining odors $>$ smelling clean air, we also tested this effect. We found significant responses
188 in the bilateral insula, putamen extending into the piriform cortices, pallidum, and orbitofrontal,
189 middle frontal, and precentral gyri, along with the left cerebellum and the right hippocampus and
190 postcentral, supramarginal, and cingulate gyri (Extended Data Fig. 1, Supplementary Table 4).

191

192

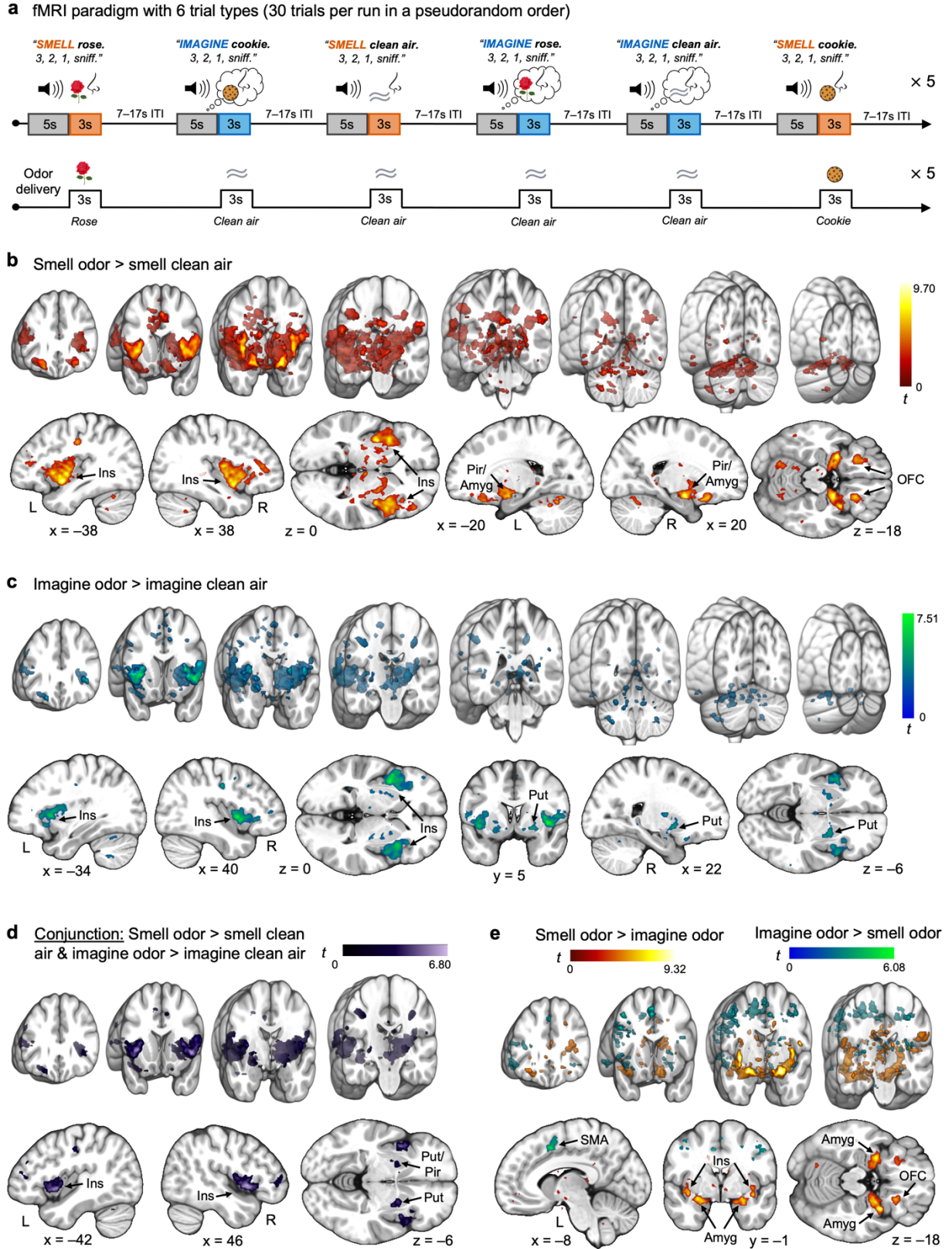
Table 1. Brain Regions with Significant Responses During Odor Imagery Versus Perception

Analysis	Left/Right Label (Brodmann Area)	Size (Voxels)	p _{FWE}	t	MNI		
					x	y	z
Imagine odor > imagine clean air	R insula posterior short gyrus	1851	<0.0001	7.514	40.5	5	0.5
	R insula anterior inferior cortex / inferior frontal gyrus (22)			7.121	48	9.5	-4
	R inferior frontal gyrus [57]			6.223	51	8	5
	L insula anterior short gyrus	1415	<0.0001	6.848	-34.5	14	0.5
	L insula anterior inferior cortex (13)			6.079	-42	8	-4
	L insula posterior short gyrus			5.935	-36	-2.5	8
	R putamen	108	0.0005	5.208	22.5	5	-5.5
	L cerebellum / dentate nucleus	75	0.0064	4.989	-16.5	-59.5	-32.5
	L cerebellum declive			4.816	-19.5	-61	-25
L cerebellum declive			3.955	-25.5	-67	-22	
<i>Conjunction:</i>	R insula anterior inferior cortex / inferior frontal gyrus	1608	<0.0001	6.804	46.5	11	-1
Smell odor > smell clean air + imagine odor > imagine clean air	R insula middle short gyrus			6.435	39	6.5	0.5
	R inferior frontal gyrus			5.654	51	8	5
	L insula anterior inferior cortex (13)	984	<0.0001	5.981	-42	5	-4
	L insula anterior short gyrus / inferior frontal gyrus (13)			5.846	-39	15.5	0.5
	L insula posterior short gyrus			5.249	-36	-2.5	8
	L precentral gyrus	55	0.0474	4.907	-39	-16	39.5
	R putamen	83	0.0045	4.702	22.5	5	-5.5
	L putamen / piriform cortex	57	0.0397	4.387	-24	3.5	-8.5
	L precentral gyrus	66	0.0181	4.159	-57	0.5	14
L precentral gyrus			4.079	-55.5	6.5	8	
<i>Difference:</i>	R uncus (38)	726	<0.0001	9.321	31.5	6.5	-17.5
Smell odor > imagine odor	R insula anterior long gyrus			8.230	37.5	2	-10
	R amygdala			7.487	22.5	-5.5	-16
	L amygdala	632	<0.0001	7.651	-28.5	2	-16
	L insula anterior inferior cortex (13)			7.642	-37.5	3.5	-10
	L insula anterior long gyrus			6.914	-39	-4	-2.5
	R posterior orbitofrontal gyrus (47)	119	<0.0001	6.050	21	24.5	-19
	R middle frontal gyrus (10)	64	0.0089	4.552	39	39.5	15.5
	R postcentral gyrus (3)	71	0.0045	4.210	60	-16	27.5
	L postcentral gyrus						
<i>Difference:</i>	L supplementary motor area	132	<0.0001	6.079	-7.5	9.5	47
Imagine odor > smell odor	L supplementary motor area (32)			3.910	-1.5	14	44
	L supplementary motor area (6)			3.682	-7.5	5	57.5

193

Bold font indicates peak voxel.

194



195

196

Fig. 3: Univariate fMRI Activity During Odor Imagery Partly Mimics that During Real Odor Perception

197 (a) Overview of the fMRI paradigm with five scan runs. Five presentations each of six trial types (30 total) were
198 pseudorandomized per run. Trials began with a 5s auditory cue including the trial type (e.g., “smell rose”) and a sniff
199 countdown of “3, 2, 1, sniff.” In the “smell” trials, participants sniffed during the 3s delivery of a rose or cookie odor or
200 clean air via an MRI-compatible olfactometer. During the “imagine” trials, they sniffed during a 3s clean air delivery. Trials
201 were separated by an intertrial interval (ITI) of 7–17s (mean = 10s).

202 (b) BOLD responses to smelling odors (rose and cookie) > smelling clean air were significant in the bilateral insula,
203 piriform/amygdala, orbitofrontal cortices, cerebellum, and middle frontal and cingulate gyri, among other regions.

204 (c) BOLD responses to imagining odors > imagining clean air (while sniffing) were significant in the bilateral insula, right
205 putamen, and left cerebellum.

206 (d) BOLD responses in the conjunction of smelling odors > smelling clean air and imagining odors > imagining clean air
207 were significant in the bilateral insula and putamen extending into the piriform cortices, along with the left precentral gyrus.

208 (e) BOLD responses to smelling odors > imagining odors were significant in the bilateral insula and amygdala and the
209 right uncus and orbitofrontal cortex, among other regions. Those to imagining odors > smelling odors were significant in
210 the left supplementary motor area.

211 Brain sections show the SPM t -map ($p_{\text{uncorrected}} < 0.005$, clusters of at least 5 voxels) overlaid onto an anatomical template
212 in MNI coordinates for illustrative purposes. In each panel, the top row depicts 3D coronal sections (18mm thick) evenly
213 spanning $y = 56$ to -88mm , and the bottom row highlights important areas of activation with custom coordinates (see
214 Table 1 and Supplementary Table 3). Color bars depict t values. L, left; R, right; Amyg, amygdala; Ins, insula; OFC,
215 orbitofrontal cortex; Pir, piriform cortex; Put, putamen.

216

217 To isolate areas of activation common to smelling and imagining odors, the comparisons
218 of smelling odors > smelling clean air and imagining odors > imagining clean air were entered
219 into a conjunction analysis using the conjunction null hypothesis. This revealed common
220 activations in the bilateral insula and putamen extending into the piriform cortices, as well as in
221 the left precentral gyrus (Fig. 3d, Table 1). We also compared the differences of smelling odors
222 > imagining odors and of imagining odors > smelling odors to isolate clusters specific to
223 perception versus imagery and vice versa. The bilateral insula and amygdala, right uncus, and
224 right lateral orbitofrontal, middle frontal, and postcentral gyri were more responsive to real
225 odors, whereas the left supplementary motor area (SMA) showed a stronger response for
226 imagined odors (Fig. 3e, Table 1). These analyses confirmed that as in odor perception, odor
227 imagery engages brain areas critical for olfactory processing, such as the piriform and insular
228 cortices.

229 Lastly, we regressed the perceptual measure of odor imagery ability (i.e., the
230 interference effect) against whole-brain univariate BOLD responses during odor imagery. We
231 did not observe any effects for imagining odors > smelling clean air. By contrast, the perceptual
232 measure of odor imagery ability was negatively associated with brain response to imagining
233 odors > imagining clean air in the right fusiform gyrus ($t_{42} = 5.038$, $p_{\text{FWE}} < 0.0001$, size = 113

234 voxels, $x = 28$, $y = -62$, $z = -14$). We did not find any significant relationships in the piriform
235 cortex, including after small-volume correction. These results suggest that odor imagery ability
236 in the current study may not correspond to the magnitude of imagined odor-evoked activity in
237 the primary olfactory cortex. They do not, however, indicate whether odor imagery ability is
238 associated with odor quality coding in this region. This is important because odor quality is
239 coded across distributed patterns of activation rather than reflected in average univariate
240 responses²⁸.

241

242 **Piriform Decoding of Imagined, but Not Actual, Odors Correlates with the Perceptual** 243 **Measure of Odor Imagery Ability**

244 To isolate fMRI patterns specific to odor quality coding, we performed MVPA in left and
245 right piriform cortex regions of interest (ROIs; Fig. 4a). We first trained and tested a support
246 vector machine (SVM) on the voxel-based patterns of activation evoked while smelling the
247 odors using a leave-one-run-out, cross-validated approach per individual (Fig. 4b). This analysis
248 revealed significant group-level decoding in the right piriform cortex (mean accuracy = 63.2%,
249 chance = 50%, $t_{43} = 2.991$, $p = 0.0046$; Fig. 4c), along with greater decoding accuracies in the
250 right compared to the left piriform cortices ($t_{43} = 2.407$, $p = 0.0205$). Next, we examined whether
251 the imagined odor qualities also activated distributed neural patterns by training and testing the
252 SVM on the voxel-based patterns of activation evoked during imagery of the two odor qualities.
253 We did not observe significant group-level decoding in either ROI (Fig. 4c). Likewise,
254 crossmodal decoding (training on real odors and testing on imagined odors, and vice versa) did
255 not produce any significant effects (Fig. 4c).

256 Leave-one-run-out cross-validation in which an SVM is trained and tested on the
257 average run-wise parameter estimates for each condition provides a relatively insensitive
258 outcome metric. For five scan runs, one decoding error reduces the accuracy estimate by 20%,
259 such that the read-out for any given participant is a multiple of this number (i.e., either 20, 40,
260 60, 80, or 100%). We therefore employed a more sensitive decoding method by analyzing the
261 split-half voxel correlations for the within-odor (e.g., smelling rose in even runs versus smelling
262 rose in odd runs) minus the between-odor (e.g., smelling rose in even runs versus smelling
263 cookie in odd runs) voxel-based activity patterns (Fig. 4d). In line with our SVM analyses, we
264 performed separate voxel correlations for real, imagined, and crossmodal odors. Again,
265 decoding accuracy was only significant for smelling real odors in the right piriform cortex ($t_{43} =$
266 3.342, $p = 0.0017$; Fig. 4e). Given that odor imagery ability varies widely across the

267 population¹⁸, the lack of main effect of imagined odor decoding is unsurprising. However, the re-
268 activation of sensory codes during imagery may occur in those individuals with vivid imagery. In
269 this case, decoding of imagined odor qualities in the piriform cortex should correlate with the
270 self-reported and perceptual measures of odor imagery ability.

271 To test this, we next examined the relationships between olfactory decoding (using the
272 split-half voxel correlations method) and the interference effect. We restricted our analyses to
273 the right piriform cortex in the 30 individuals with discriminable neural patterns for actual odors
274 to ensure that any effects would not be driven by an inability to decode altogether. We observed
275 a strong positive association between right piriform decoding of imagined odors and our
276 perceptual measure of odor imagery ability (i.e., the interference effect; Fig. 4f). Similar
277 analyses using the self-report measures of odor ($p = 0.0571$) and flavor ($p = 0.0722$) imagery
278 ability approached significance. In contrast, there were no significant associations between the
279 perceptual or self-report measures of odor imagery ability and the fMRI patterns evoked during
280 actual odor presentations (Fig. 4g) or in the crossmodal datasets (Fig. 4h). The results remained
281 largely unchanged when including the full sample ($n = 44$; Supplementary Table 5). Imagined
282 odor decoding was also unrelated to the demographic variables, olfactory function, odor ratings,
283 sniff parameters, hunger, and typical consumption of unhealthy foods (Supplementary Table 1).
284 Collectively, these data demonstrate that odor imagery ability is associated with successful
285 activation of distinct imagined odor quality codes in the right piriform cortex.

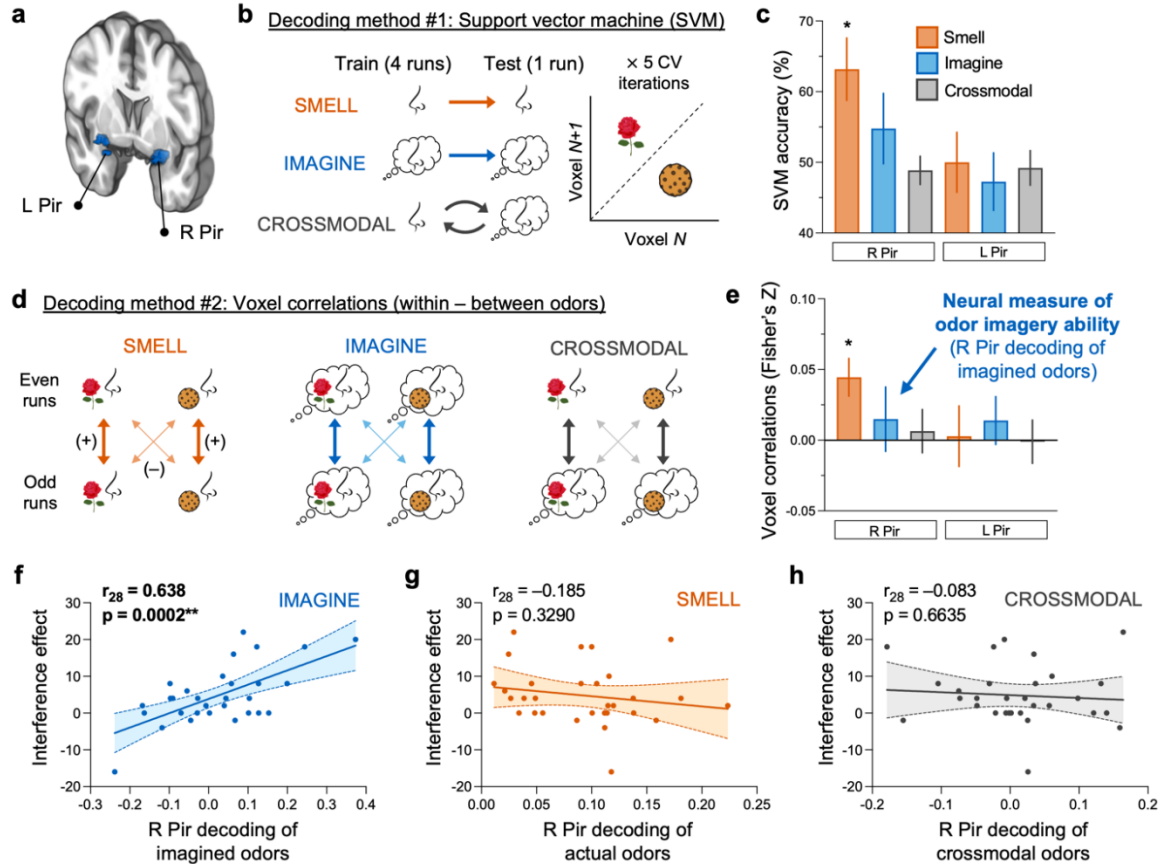


Fig. 4: Decoding of Imagined, but Not Actual, Odors in the Right Piriform Cortex Provides a Neural Measure of Odor Imagery Ability.

(a) Regions of interest for the neural decoding analyses.

(b) SVMs were trained to classify rose versus cookie using data from four runs and tested on data from the fifth left-out run across five CV iterations. In the “smell odor” and “imagine odor” conditions, SVMs were trained and tested on voxel patterns from the same modality (actual odors and imagined odors, respectively). For crossmodal decoding, the SVM was trained on real odor patterns and tested on imagined odor patterns (and vice versa).

(c) SVM accuracies for smelling actual odors in the right piriform cortex were significant at the group-level.

(d) Split-half Fisher’s Z-transformed voxel correlations calculated between odor (e.g., smelling the rose odor in even runs versus smelling the cookie odor in odd runs) were subtracted from those calculated within odor (e.g., smelling the rose odor in even versus odd runs) as a more sensitive index of neural decoding.

(e) Voxel correlations for smelling actual odors in the right piriform cortex were significant at the group-level.

(f–h) The perceptual measure of odor imagery ability (i.e., the interference effect) positively correlated with right piriform decoding of imagined (f), but not real (g) or crossmodal (h), odors using voxel correlations (decoding method #2).

Bar plots represent $M \pm SEM$. Fitted scatterplots depict single participants and the 95% CI. L, left; R, right; Ins, insula; Pir, piriform; CV, cross-validation. * $p < 0.01$; ** $p < 0.001$.

286

287

288

289

290

291

292

293

294

295

296

297

298

299

300

301

302

303

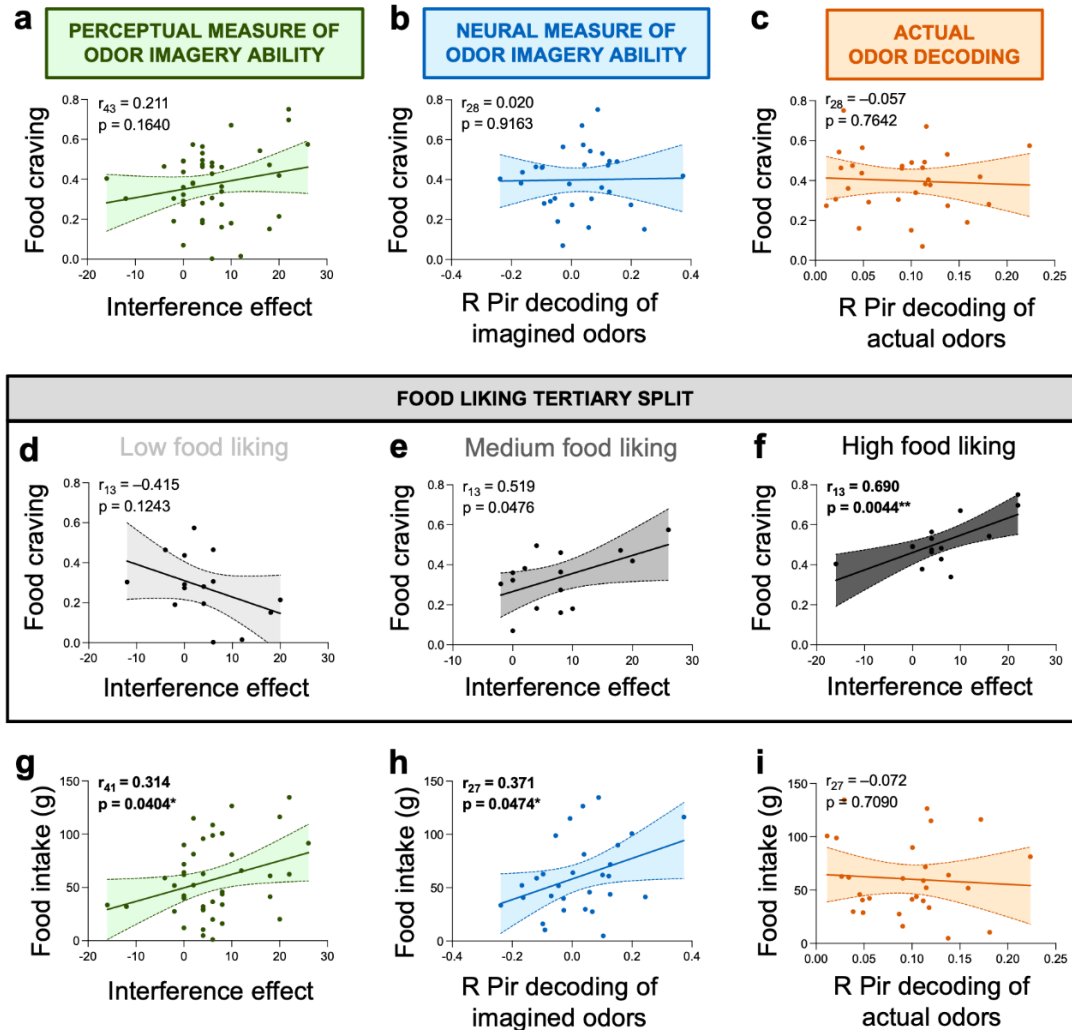
304

305 **Odor Imagery Ability is Associated with Stronger Food Cravings for Liked Foods**

306 To test our prediction that odor imagery ability is associated with food cue reactivity, we
307 used a measure of cue-induced food craving in which participants were asked to rate the
308 strength of their craving in response to the presentation of 90 palatable food images³¹ (see
309 example stimuli in Fig. 1b). We found no significant relationships between the perceptual
310 measure of odor imagery ability (i.e., the interference effect; Fig. 5a) or the neural measure of
311 odor imagery ability (i.e., right piriform decoding of imagined odors; Fig. 5b) and the average
312 rating of food craving strength. Likewise, the decoding of actual odors in the right piriform cortex
313 was unrelated to food craving (Fig. 5c).

314 However, the rated liking of the foods depicted in the pictures was variable and
315 significantly correlated with craving (Supplementary Table 6). We therefore reasoned that odor
316 imagery may intensify cravings specifically for foods that are liked and constructed a linear
317 regression model to test for the presence of an interaction between odor imagery and food liking
318 on the average craving rating. As predicted, the interaction was significant for the perceptual
319 measure of odor imagery ability ($t_{41} = 2.918$, $p = 0.0057$) and approached significance for the
320 neural measure ($t_{26} = 1.835$, $p = 0.0780$). For graphical purposes and to better understand the
321 nature of this interaction, we used a tertiary split ($n = 15$ each) to separate participants based on
322 their average food liking rated on the Labeled Hedonic Scale (LHS)³³. In the low liking group
323 (mean LHS rating = -0.17 , range = -66.60 to 11.68), there was no correlation between the
324 perceptual measure of odor imagery ability and food craving (Fig. 5d). In the medium liking
325 group (mean LHS rating = 19.52 , range = 11.83 to 27.98), a positive trend emerged that was not
326 significant after correction for multiple comparisons (Fig. 5e). In contrast, the high liking group
327 (mean LHS rating = 37.69 , range = 29.85 to 48.98) showed a strong positive association even
328 after correction for multiple comparisons (Fig. 5f).

329 We also performed a follow-up analysis using a linear mixed effects model with the
330 individual ratings for each of the 90 food pictures rather than participant averages. Craving was
331 designated as the outcome variable; the interference effect, food liking, and the interaction of
332 the two as fixed effects; and participant as a random effect. Testing this model once again
333 revealed a significant interaction effect ($F_{1,3996} = 7.571$, $p = 0.0060$) whereby cravings for liked
334 but not disliked foods were more intense in individuals with vivid odor imagery. In addition,
335 accounting for subjective hunger ratings – which were positively correlated with food craving
336 (Supplementary Table 6) – did not impact any of the results. Collectively, these data suggest
337 that good odor imagery ability paired with high food liking may give rise to intense food cravings.



338

339

Fig. 5: Odor Imagery Ability Contributes to Food Cue Reactivity

340

(a–c) Food craving did not correlate with the perceptual (a) or neural (b) measures of odor imagery ability or with actual odor decoding (c).

341

342

(d–f) There was a significant interaction between food liking and the perceptual measure of odor imagery ability on craving ($p = 0.0057$). Following a tertiary split to separate participants by their average food liking, the interference effect was unrelated to food craving in the low (d) and medium (e) food liking groups after Bonferroni correction for the three tests performed. By contrast, there was a positive correlation in the high food liking group (f).

343

344

345

346

(g–i) Food intake positively correlated with the perceptual (g) and neural (h) measures of odor imagery ability, but not with actual odor decoding (i).

347

348

Fitted scatterplots depict single participants and the 95% CI. R, right; Pir, piriform; LHS, Labeled Hedonic Scale³³. * $p < 0.05$; ** $p < 0.01$.

349

350

351 **Odor Imagery Ability Correlates with Cue-Potentiated Food Intake**

352 Having identified a role for odor imagery ability in food craving, we next tested for
353 associations with our second measure of food cue reactivity, cue-potentiated food intake. We
354 performed a validated bogus taste test³² in which participants were presented with two plates of
355 cookies. They were instructed to sample as much as they wanted while responding to questions
356 about the sensory properties of the cookies. They were not told that the real purpose of the test
357 was to quantify how much was consumed in grams. In line with our expectations, the perceptual
358 ($r_{41} = 0.314$, $p = 0.0404$; Fig. 5g) and neural ($r_{27} = 0.371$, $p = 0.0474$; Fig. 5h) measures of odor
359 imagery ability were each positively associated with food intake. Additionally, we performed
360 separate linear regressions to adjust for sex – since males ate more than females – and cookie
361 liking ratings, which were positively correlated with the amount consumed (Supplementary Table
362 6). Both the perceptual ($\beta = 0.351$, $p = 0.0098$) and neural ($\beta = 0.420$, $p = 0.0136$) measures of
363 odor imagery ability remained as significant predictors of intake in these models. Interestingly,
364 right piriform decoding of actual odors was unrelated to cookie consumption ($r_{27} = -0.072$, $p =$
365 0.7090 ; Fig. 5h). These findings indicate that the association is specific to odor quality codes
366 evoked during imagery.

367

368 **Neurobiological Craving Signature Responses are Stronger while Imagining a Food** 369 **Versus Nonfood Odor**

370 To build upon our use of two behavioral food cue reactivity measures, our next step was
371 to explore the extent to which smelling versus imagining odors elicits brain food cue reactivity.
372 We assessed brain food cue reactivity using the Neurobiological Craving Signature (NCS), a
373 multivariate brain pattern that reliably predicts self-reported drug and food craving across
374 independent samples²⁹. We tested a version of the NCS trained only on visual food cues and
375 identified the 'pattern response' value for each participant and fMRI contrast in the current
376 study. This pattern response describes the similarity of the participant's contrast image (e.g.,
377 while imagining odors) to the NCS and therefore the predicted level of food craving for that
378 individual. As such, greater NCS pattern responses indicate stronger similarity to the craving
379 map and higher predicted levels of food craving. Although the NCS is capable of distinguishing
380 drug users from non-users in prior work, it was not primarily trained to detect individual
381 differences in craving. NCS pattern responses also partially depend on factors such as overall
382 fMRI signal³⁴, which differed in coverage of the parietal lobe across participants in the current
383 study (Extended Data Fig. 2a). However, NCS pattern responses are particularly well suited for

384 assessing the impacts of within-subject interventions or contrasting contexts (e.g., examining
385 their modulation by condition, such as smelling versus imagining the odor types and clean air).

386 In testing the latter, we found significant main effects of perceptual modality
387 (smelling/imagining; $F_{1,258} = 7.765$, $p = 0.0057$) and odor type (rose/cookie/clean air; $F_{2,258} =$
388 9.716 , $p < 0.0001$) and an interaction of the two ($F_{2,258} = 4.100$, $p = 0.0177$; Extended Data Fig.
389 2b) on NCS pattern responses. Follow-up comparisons revealed significantly greater NCS
390 pattern responses to smelling versus imagining the cookie ($t_{86} = 3.192$, $p = 0.0020$) and rose (t_{86}
391 $= 4.593$, $p < 0.0001$) odors, with no difference in smelling versus imagining clean air ($t_{86} = 0.376$,
392 $p = 0.7077$). Smelling both the rose ($t_{86} = 3.078$, $p = 0.0028$) and cookie ($t_{86} = 3.862$, $p = 0.0002$)
393 odors resulted in greater NCS pattern responses than smelling clean air. In contrast, neither
394 imagining the cookie ($t_{86} = 0.753$, $p = 0.0832$) nor the rose ($t_{86} = 0.499$, $p = 0.6193$) odor yielded
395 greater NCS pattern responses than imagining clean air. However, imagining the cookie odor
396 did elicit stronger NCS pattern responses than imagining the rose odor ($t_{86} = 3.068$, $p = 0.0029$),
397 an effect that did not occur for smelling the cookie versus rose odor ($t_{86} = 0.428$, $p = 0.6695$).
398 These discrepancies suggest that the brain signature for craving is weaker during odor imagery
399 than during real perception. Yet it may also be more finely tuned to food versus nonfood cues,
400 such that the craving level predicted by the NCS is greater for food odors than nonfood odors
401 during olfactory imagery.

402

403 **Odor Imagery Ability is Not Related to Current Adiposity**

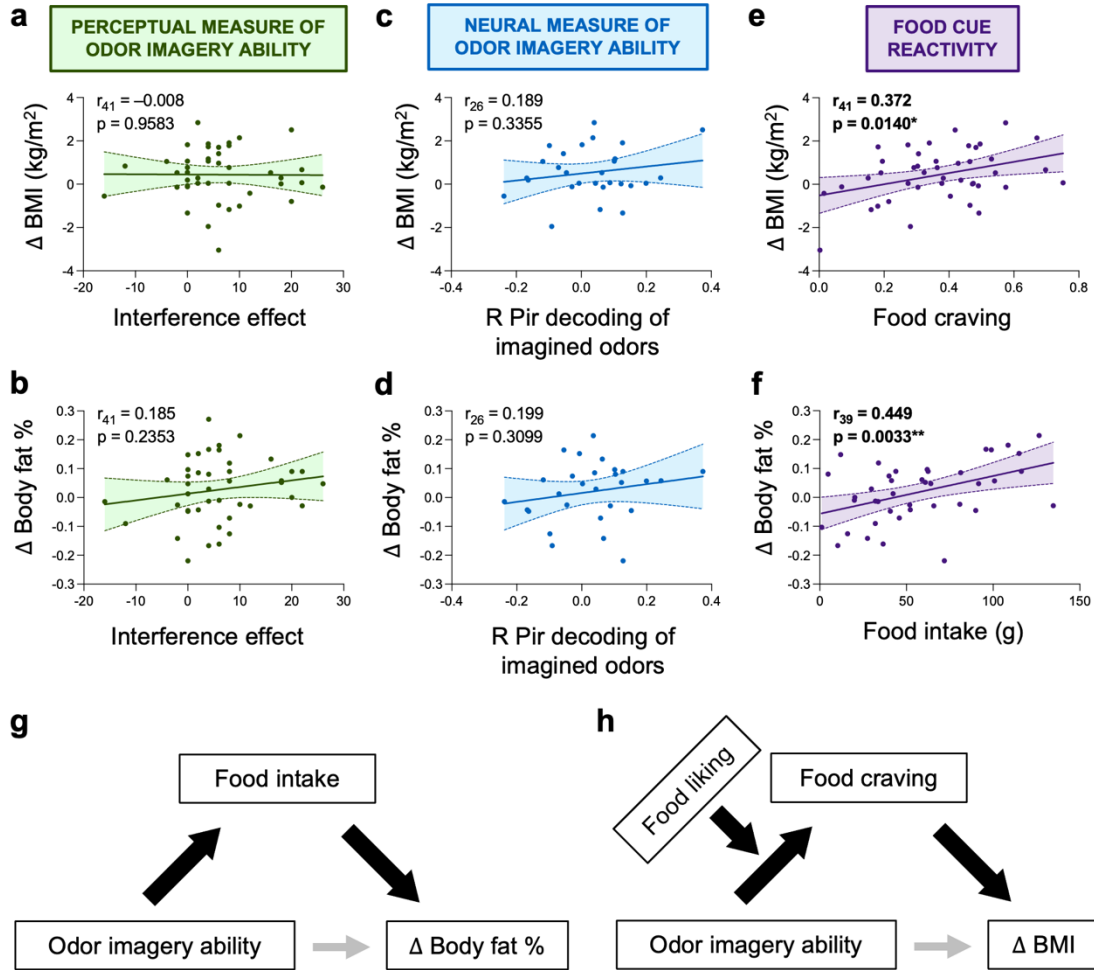
404 In contrast with prior work²⁰, the self-reported, perceptual, and neural measures of odor
405 imagery ability were not significantly associated with current adiposity defined by BMI or body
406 fat percentage (Supplementary Table 1). However, we speculated that the variance in BMI
407 within the current participant sample (BMI: $M = 26.12$, $SD = 6.81$, Range = 18.32–53.44 kg/m²)
408 may have differed from that across the two experiments (BMI: $M = 25.75$, $SD = 5.06$, Range =
409 17.70–38.70 kg/m²) in the previous study comparing VOIQ score with BMI²⁰. To test this, we
410 used a two-sample F-test for equal variances and found that the BMI variance in the present
411 study was significantly greater than in the prior study ($F_{44,81} = 1.810$, $p = 0.0210$). As the causes
412 of obesity are heterogeneous, one possible explanation for the lack of a significant correlation
413 between odor imagery ability and current adiposity here could be the inclusion of participants
414 across a wider range of BMIs.

415

416 **Food Cue Reactivity Mediates the Relationship between Odor Imagery Ability and**
417 **Adiposity Change**

418 In the previous analyses, we demonstrate that odor imagery ability is associated with
419 food cue reactivity but not current adiposity. To test our overarching hypothesis that odor
420 imagery ability intensifies food cravings and increases consumption to promote longer-term
421 weight gain, we first used correlation analyses to assess the relationships among these
422 variables. Neither measure of odor imagery ability was significantly correlated with changes in
423 BMI or body fat percentage over one year from the baseline to follow-up sessions (Fig. 6a-d).
424 Food craving in the cue-induced craving paradigm was also not associated with cue-potentiated
425 food intake in the bogus taste test ($r_{41} = 0.255$, $p = 0.0983$). However, food craving predicted
426 changes in BMI (Fig. 6e) but not body fat percentage ($r_{41} = 0.229$, $p = 0.1402$), whereas food
427 intake predicted changes in body fat percentage (Fig. 6f) but not BMI ($r_{39} = 0.263$, $p = 0.0964$).
428 Accounting for age – which was positively correlated with change in BMI (Supplementary Table
429 7) – did not impact any of the results. Additionally, changes in adiposity were unrelated to sex,
430 household income, olfactory function, food liking, typical consumption of unhealthy foods, and
431 changes in physical activity over the year (Supplementary Table 7).

432 Given the lack of significant direct effects between odor imagery ability and change in
433 adiposity, we tested for indirect effects via food cue reactivity across three models. The results
434 are summarized in Table 2. Consistent with our hypotheses, cue-potentiated food intake
435 mediated the associations between both the perceptual (Model 1) and neural (Model 2)
436 measures of odor imagery ability and change in body fat percentage (Fig. 6g). In Model 3, we
437 tested whether food craving mediated the relationship between the perceptual measure of odor
438 imagery ability and change in BMI, though here we used moderated mediation to account for
439 the effect of liking on the association between odor imagery ability and craving (Fig. 6h).
440 Specifically, food liking was included as a moderator of the a-path. The index of moderated
441 mediation – indicating whether the strength of the indirect effect between odor imagery ability
442 and change in BMI via food craving depended on the level of food liking – was significant (Table
443 2). In other words, better odor imagery ability resulted in greater changes in BMI through
444 heightened food craving, but only in individuals who liked such high-fat, high-sugar foods. Taken
445 together, these mediation and moderated mediation models provide evidence that odor imagery
446 ability drives variation in food cue reactivity strength, which in turn influences risk for increased
447 adiposity.



448

449 **Fig. 6: Food Cue Reactivity Mediates the Relationships between Odor Imagery Ability and Changes**
 450 **in BMI and Body Fat Percentage**

451 (a–b) The perceptual measure of odor imagery ability did not correlate with change in BMI (a) or body fat percentage (b).

452 (c–d) The neural measure of odor imagery ability did not correlate with change in BMI (c) or body fat percentage (d).

453 (e–f) Food craving positively correlated with change in BMI (e), whereas food intake positively correlated with change in
 454 body fat percentage (f).

455 (g–h) Visualizations of the mediation (g) and moderated mediation (h) models. In both, there was no direct effect between
 456 odor imagery ability and adiposity change (thin gray arrows), but the indirect effects via food cue reactivity (thick black
 457 arrows) were significant, conditional by food liking in g. Panel g corresponds to Models 1 and 2 and panel h corresponds
 458 to Model 3 from Table 2.

459 Fitted scatterplots depict single participants and the 95% CI. R, right; Pir, piriform. * $p < 0.05$; ** $p < 0.01$.

460

Table 2. Mediation and Moderated Mediation Models

#	Model Path/Effect: Predictor → Outcome	β	SE	LL	UL
1	a: Perceptual measure of odor imagery ability → Food intake	0.350	0.133	0.081	0.620
1	b: Food intake → Δ Body fat %	0.505	0.182	0.136	0.874
1	c' Direct: Perceptual measure of odor imagery ability → Δ Body fat %	0.019	0.160	-0.306	0.345
1	a × b Indirect: Perceptual measure of odor imagery ability → Food intake → Δ Body fat %	0.177	0.091	0.031	0.382
2	a: Neural measure of odor imagery ability → Food intake	0.407	0.166	0.063	0.751
2	b: Food intake → Δ Body fat %	0.722	0.221	0.264	1.181
2	c' Direct: Neural measure of odor imagery ability → Δ Body fat %	-0.120	0.198	-0.530	0.290
2	a × b Indirect: Neural measure of odor imagery ability → Food intake → Δ Body fat %	0.294	0.160	0.022	0.647
3	a: Perceptual measure of odor imagery ability → Food craving	-0.180	0.133	-0.449	0.090
3	Moderation: Perceptual measure of odor imagery ability × Food liking → Food craving	0.368	0.112	0.141	0.595
3	b: Food craving → Δ BMI	0.439	0.174	0.087	0.790
3	c' Direct: Perceptual measure of odor imagery ability → Δ BMI	-0.082	0.154	-0.393	0.230
3	Conditional a × b indirect (Low food liking): Perceptual measure of odor imagery ability → Food craving → Δ BMI	-0.079	0.103	-0.347	0.055
3	Conditional a × b indirect (Moderate food liking): Perceptual measure of odor imagery ability → Food craving → Δ BMI	0.033	0.103	-0.347	0.158
3	Conditional a × b indirect (High food liking): Perceptual measure of odor imagery ability → Food craving → Δ BMI	0.184	0.109	0.011	0.434
3	Index of moderated mediation: Perceptual measure of odor imagery ability × Food liking → Food craving → Δ BMI	0.161	0.104	0.007	0.411

461

462

463

464

465

We controlled for sex and food liking in Models 1 and 2 and for hunger in Model 3 since these variables were correlated with food cue reactivity (see Supplementary Table 6). Models 1 and 2 are visually depicted in Fig. 6g and Model 3 in Fig. 6h. LL, confidence interval lower limit; UL, confidence interval upper limit. Bold font indicates significant effects at $p < 0.05$.

466 DISCUSSION

467 It is well established that food cue reactivity including craving is associated with weight
468 gain susceptibility⁵, but the mechanisms underlying this relationship are poorly understood. The
469 current study was motivated by the proposed role for mental imagery in craving intensity⁶ and
470 the existence of significant variation in odor imagery ability¹⁸ that is positively associated with
471 BMI²⁰. These previous observations led us to hypothesize a role for olfactory imagery in driving
472 food cue reactivity strength to promote weight gain. Our results support this hypothesis by
473 demonstrating an indirect link between odor imagery ability and one-year change in adiposity
474 via food cue reactivity. We also show that this effect is selective to imagined odors, as it does
475 not generalize to perceptually experienced odors or to visual imagery.

476 Mental imagery involves “top-down” reactivation of sensory circuits^{35–42} and is thought to
477 help optimize adaptive behavior through simulations of future actions based on past
478 experiences⁴³. In the context of ingestive behavior, food choice depends upon a complex
479 integration of internal and external signals⁴⁴. Imagining what to eat may contribute to food
480 decisions by enabling simulations of the predicted sensory pleasure and eventual nutritive value
481 of eating a potential energy source relative to the current homeostatic state of the organism
482 (e.g., hungry or sated). Thus, imagery facilitates the weighing of the costs and benefits that
483 determine decisions. Indeed, recent preclinical work demonstrates that food odor exposure
484 stimulates lipid metabolism but only in fasted animals with functioning olfactory memory⁴⁵.
485 Perhaps olfactory memory – a key component of imagery – has the same effect on preparing
486 the body for anticipated intake in humans (and thereby enhancing motivation for food). Our
487 findings suggest that in an environment laden with food cues, the ability to form vivid mental
488 images of the smell and flavor of foods promotes overeating.

489 In our study, olfactory imagery ability was assessed by multiple measures that correlated
490 with each other and therefore support construct validity. The association between the perceptual
491 measure (i.e., the interference effect) and the neural measure (i.e., right piriform decoding of
492 imagined odors) was particularly strong (Fig. 4f). This suggests that piriform quality coding is
493 critical for, and contributes to the variability in odor imagery ability that has been reported by a
494 number of independent studies^{15–19}. Notably, we restricted our correlation analyses to the right
495 piriform cortex because decoding of real odors in this region was significantly greater than both
496 chance level and decoding in the left piriform cortex. This finding is in accordance with evidence
497 for right hemispheric dominance over olfactory processing in general^{46,47}, odor memory^{48–50}, and
498 the decoding of real odor quality^{51,52}.

499 In contrast to our prediction, the crossmodal decoding was not above chance level,
500 meaning that the patterns generated by imagining the odors could not be decoded using the
501 patterns generated by the actual perception of those same odors. One possible explanation for
502 this finding is that the imagined odors only reactivate odor identity while the real odors reactivate
503 odor identity plus the coding of the physiochemical odorant properties occurring across separate
504 subpopulations of piriform cortex neurons⁵³. Similar distinctions are observed between imagined
505 and actual coding in other sensory modalities. For example, the neural substrates for the
506 decoding of place memories are immediately anterior to those for real-time scene perception⁵⁴.
507 Likewise, visual imagery engages only a subset of regions contributing to visual perception⁵⁵.
508 Decoding studies at higher magnetic field strength with smaller voxel sizes would be helpful in
509 testing this possibility.

510 Our univariate results also align with prior work in olfactory imagery demonstrating
511 responses in the piriform olfactory cortex while imagining odors versus smelling clean air^{22,56,57}.
512 It is important to note that in the current study, as well as in prior work, the perceptual measure
513 of odor imagery ability (i.e., the interference effect) did not correspond to the magnitude of
514 piriform responses to imagined odors. By contrast, we observed a strong association between
515 the interference effect and imagined odor quality decoding in the right piriform cortex. This
516 suggests that it is these quality codes that underlie imagery, with univariate responses likely
517 including other factors such as sniffing, attention, and associative learning⁵⁸. Accordingly, we
518 ensured that sniffing did not impact our perceptual or neural measures of odor imagery ability.
519 This is critical because sniffing induces piriform activity⁵⁹ and is necessary for the generation of
520 vivid odor imagery^{60,61}. Individuals with better odor imagery ability take larger sniffs while
521 imagining pleasant versus unpleasant smells, a modulatory pattern that is not seen in poor odor
522 imagers⁶². Here we specifically selected pleasant odors to minimize potential sniffing
523 differences.

524 With respect to attention, the frontal piriform cortex and olfactory tubercle respond
525 preferentially to attended compared to unattended sniffs^{63,64}. In the current study, we instructed
526 participants to sniff in each trial – irrespective of smelling or imagining – prompted by an
527 auditory cue to equate attentional demands. Finally, although visual cues that have been
528 associated with specific odors are capable of evoking piriform⁶⁵ and olfactory bulb⁶⁶ responses,
529 we found that the interference effect correlated with self-reported odor and flavor, but not visual,
530 imagery and that visual imagery did not interfere with detecting an incongruent odor.
531 Collectively, these data support the conclusion that imagined odor-evoked quality codes in

532 piriform cortex underlie variation in imagery ability rather than non-specific effects such as
533 sniffing, attention, or sensory associative learning.

534 The principal finding in the current study is that the generation of distinguishable
535 imagined odor quality codes in the piriform cortex correlates not only with imagery ability, but
536 also with measures of food cue reactivity that in turn predict change in adiposity. We therefore
537 propose that better odor imagery leads to stronger food craving and greater intake that
538 promotes obesity risk (Fig. 1c). Accordingly, our mediation analyses revealed that better odor
539 imagery ability does not directly lead to larger adiposity change, but rather that it exerts an
540 influence via a food cue reactivity-dependent mechanism. These results back the Elaborated
541 Intrusion Theory of Desire, which posits that effortful cognitive elaboration of food properties
542 through imagery intensifies cravings⁶. They also corroborate studies showing that vivid sensory
543 imagery is linked to a strong desire for foods, drugs, and alcohol^{7-13,67}. However, they are the
544 first to isolate odor-specific imagery as the critical contributor to food cue reactivity.

545 The current findings are also relevant to the ongoing work linking olfactory function with
546 risk for weight gain. Although many associations have been reported, the direction is not
547 consistent. Reports for positive⁶⁸⁻⁷³, negative⁷⁴⁻⁸¹, or no^{82,83} relationship between olfaction and
548 food intake, current BMI, or weight change have been made. Here we found that olfactory
549 function – defined either as detection thresholds or as piriform decoding of actual odor quality –
550 was unrelated to any measure of odor imagery ability, food cue reactivity, or adiposity change.
551 The same was true for suprathreshold perceptual ratings of odor intensity, familiarity, liking, and
552 edibility. Thus, our results suggest that olfactory simulations or imagery may drive the
553 relationship rather than olfactory coding or perception *per se*, which could account for the
554 inconsistencies that have been noted previously.

555 For example, imagining what to eat may allow an organism to test the impact of
556 available energy sources on their perceived hunger, pleasure, or mood before selecting which
557 item to consume. It is well known that olfaction is tightly coupled to emotional valence⁸⁴, and
558 odor imagery ability positively correlates with the experience and processing of emotion^{16,85}. The
559 presence of reward-related cues during motor imagery enhances neural activity in and
560 functional connectivity between the motor cortex and ventral striatum, giving rise to a
561 mechanism by which the imagery may become motivationally salient enough to yield action⁸⁶.
562 While we did not measure emotional reactivity or salience in the current study, we did quantify
563 food liking and observed a moderating effect of this variable. Specifically, we found that better
564 odor imagery ability corresponds to more intense food cravings and larger weight gain in

565 individuals who exhibit strong liking of the high-fat/high-sugar foods that we tested. It is
566 therefore likely that odor imagery interacts with pleasure to invigorate food cravings.

567 Another possibility is that odor imagery bridges current states with future simulations in
568 guiding food choice through the involvement of the SMA and insula. The SMA is linked to motor
569 planning^{87,88}, while the insula plays a role in interoception and the prediction of bodily states^{89–91}.
570 For instance, food cues elicit transient activity across populations of insular neurons that mimics
571 future metabolic conditions⁹² and is necessary for driving food seeking behaviors⁹³ in mice. In
572 humans, the SMA and insula are not only consistently activated during mental imagery^{22,94–103},
573 but also during food and drug craving^{14,104–109}.

574 Here we identified extensive clusters of activity in the insula preferentially responding to
575 imagining odors versus clean air. Moreover, the left SMA was the only whole-brain-corrected
576 region exhibiting stronger activity while imagining versus smelling odors. These results are in
577 line with the responsivity of the insula and SMA to imagined versus perceived odors in prior
578 work^{22,110}. We also found that the pattern responses predicted by the recently developed
579 Neurobiological Craving Signature²⁹, which has positively weighted voxels in both the insula and
580 SMA (among other regions), were greater while imagining a food versus a nonfood odor. These
581 data lead to the hypothesis that information from the coding of imagined odors in the piriform
582 cortex is relayed to the insula and SMA to simulate future interoceptive states and food
583 decisions, promoting the cravings and physiological changes (e.g., ghrelin release) that trigger
584 subsequent consumption. The direct links between the piriform cortex, insula, and SMA and the
585 general validity of this model warrant future testing.

586 Imagery requires memory systems to pull from past experiences in simulating the future.
587 Though we screened participants for self-reported cognitive deficits or memory loss that could
588 impact mental imagery, we did not explicitly measure memory capacity in the current study.
589 Impaired memory and hippocampal function are hallmark characteristics in the development of
590 obesity¹¹¹. A recent study reported that despite showing disrupted memory for non-food items,
591 individuals with obesity outperform their lean counterparts in memory for food items¹¹².
592 Importantly, memory was not associated with the perceived vividness of imagining scenes
593 corresponding to the food or non-food cues in that study¹¹². The indirect effect of odor imagery
594 ability on change in BMI that we observed here is therefore unlikely linked to memory function,
595 though this should be tested in the context of olfactory imagery in future work. As obesity-
596 related memory alterations may particularly stem from poor diet^{113,114}, the subsequent question
597 emerges of whether frequent consumption of high-fat/high-sugar foods impacts odor imagery
598 ability. Studies do suggest that experience can improve imagery ability, with expert chefs¹¹⁵,

599 perfumers¹¹⁶, and sommeliers¹¹⁷ exhibiting more vivid odor imagery or functional reorganization
600 in its neural correlates. Here we found no relationship between odor imagery ability and typical
601 consumption of energy-dense foods measured with the Dietary Fat and Free Sugar Short
602 Questionnaire¹¹⁸ or following the craving or bogus taste test measures. However, future studies
603 should examine the prospective effects of dietary manipulations on odor and flavor imagery
604 ability and, in turn, on food cue reactivity and obesity risk. Food cue reactivity across a wider
605 range of items including nutritional foods should also be considered since there is evidence for
606 increased attention and memory¹¹⁹ or selection and intake³¹ of healthy foods following
607 manipulations to sensory appeal or training in cognitive regulation strategies, respectively.

608 Finally, we note that the current findings have relevance for obesity treatment. One of
609 the leading behavioral strategies for decreasing food cue reactivity is cue exposure therapy
610 (CET)². In CET, patients are trained to refrain from eating their most desired foods during
611 exposure in a controlled setting, thereby extinguishing the learned associations between food
612 cues and consumption. While CET is effective for exposed cues, reductions in food cue
613 reactivity including intake do not generalize to unexposed foods^{120,121}, limiting the potential for
614 weight loss. Our study demonstrates that odor imagery could serve as a novel behavioral
615 therapy target with the VOIQ as a simple tool for screening susceptible individuals. Cognitive
616 tasks that compete with odor imagery may be particularly fruitful in disrupting food cue
617 reactivity¹²². For instance, prior research has shown that imagining the memory of a time that a
618 snack was avoided or thinking about the future consequences of consumption can help to
619 reduce intake in the moment^{123,124}. We propose that imagery in the same sensory modality, such
620 as imagining a nonfood odor or one that is disliked, may prove especially successful in limiting
621 the capacity for flavor imagery to strengthen food cravings.

622

623 **Concluding Remarks**

624 In conclusion, the results of our study highlight a role for odor imagery ability in obesity
625 risk via food cue reactivity and point to coding in the piriform primary olfactory cortex as the
626 neural substrate. Future work should explore the extent to which odor imagery helps to integrate
627 internal and external metabolic signals and investigate the efficacy of odor imagery being an
628 additional behavioral target for weight loss therapy.

629

630

631 MATERIALS AND METHODS

632 Participants

633 A flow diagram depicting the number of individuals at each stage of the study (e.g.,
634 eligibility, recruitment, completion, analysis) is provided in Extended Data Fig. 3. Participants
635 were recruited from the local New Haven, CT, USA community and university population via
636 flyer and social media advertisements. Individuals interested in this study or other previous
637 studies in our lab filled out an online form using Qualtrics software (Qualtrics, UT, USA) to
638 indicate initial information such as their sex assigned at birth, age, estimated BMI, drug use, etc.
639 We pre-screened subjects in this database to identify individuals free from known taste or smell
640 dysfunction, dieting behaviors, food restrictions, nicotine or drug use, serious medical conditions
641 including metabolic, neurologic, and psychiatric disorders or medications used to treat these,
642 cognitive deficits or memory loss that could impact mental imagery, and any MRI-
643 contraindications (e.g., being left-handed, pregnant, or having metal in the body). We then
644 assessed for further eligibility with follow-up email questions (e.g., to ensure that these people
645 did not note any new disorders or drug use, recent smell loss due to COVID-19, or intent to
646 leave the greater New Haven, CT area). To capture similar individuals across a range of BMIs,
647 we used stratification to minimize differences in sex, race, ethnicity, age, and household income
648 among individuals recruited into 2 BMI groups (low BMI < 25 and high BMI ≥ 25 kg/m²).

649 For the perceptual measure of odor imagery ability, 36 participants completed all
650 imagery conditions based on a power analysis performed in G*Power version 3.1.9.6^{125,126} to
651 replicate the interference effect ($d = 0.722$) from the prior task validation²¹ in the low and high
652 BMI groups ($n = 18$ each) at 0.80 power ($\alpha = 0.05$, two-tailed test, two dependent means).
653 Twelve additional participants were then recruited to complete only the odor imagery condition
654 and all other study measures (with one excluded from scanning due to extreme claustrophobia).
655 This was sufficient to achieve 0.80 power ($n = 42$, $\alpha = 0.05$, two-tailed test, bivariate normal
656 model) for the effect observed between self-reported odor imagery ability and obesity risk ($r =$
657 0.42) in previous work²⁰. Data from three participants were removed due to an inability to obtain
658 proper odor thresholds such that their detection accuracies fell below chance level (less than
659 50% correct responses). Participant characteristics of the final sample ($N = 45$) by BMI group
660 are provided in Supplementary Table 8. All individuals provided written informed consent, and
661 the study procedures were approved by the Yale Human Investigations Committee (Institutional
662 Review Board Protocol # 0405026766). The study was also preregistered (AsPredicted.org
663 #56278).

664

665 **Stimuli**

666 Odors included “phenylethyl alcohol white extra” (rose, #001059147) and “cookie dough”
667 (cookie, #10610208) from International Flavors and Fragrances (New York, NY, USA) diluted in
668 food-grade propylene glycol. The bogus taste test consisted of eight “Grandma’s Homestyle
669 Chocolate Chip Cookies” broken into bite-sized pieces across two plates (for a total of ~280g or
670 ~1360 kcal) presented alongside a 16 fl oz water bottle.

671

672 **Experimental Procedures**

673 The study consisted of three behavioral sessions and one fMRI scan at baseline, along
674 with a follow-up session one year later. Full data collection from the first (baseline) to last
675 (follow-up) sessions spanned 10/6/2020–6/3/2022. The fMRI scan was scheduled between
676 8:00am-1:00pm, and all other sessions took place between 8:00am-8:00pm. We ensured that
677 food craving and intake were assessed between the hours of 11:30am-7:00pm. Individuals were
678 instructed to arrive to all sessions neither hungry nor full, but at least one-hour fasted.

679 Behavioral Sessions

680 *Training and Scales.* Participants were first trained to make computerized ratings in
681 PsychoPy version 3.0¹²⁷ by practicing with imagined sensations (e.g., the taste of your favorite
682 chocolate) and real stimuli (e.g., the brightness of the ceiling light or the pressure of a weight).
683 Intensity and liking were rated with the vertical category-ratio general Labeled Magnitude Scale
684 (gLMS)^{128–130} and Labeled Hedonic Scale (LHS)³³, respectively. The gLMS ratings were log
685 base 10 transformed prior to any analyses. All other ratings were made on horizontal visual
686 analog scales (VAS). Familiarity and edibility were rated from “not at all familiar” to “more
687 familiar than anything” and from “not at all” to “more than anything” in response to “how much do
688 you want to eat this?”, respectively. Internal state ratings for hunger, fullness, thirst, anxiety, and
689 need to urinate were made from “not at all [hungry/full/etc.]” to “more [hungry/full/etc.] than
690 anything.” Subjective hunger was calculated as the difference of VAS ratings for hunger –
691 fullness. Participants also practiced one odor run in a mock MRI simulator in the lab.

692 *Adiposity.* Body weight was measured with an electronic scale and height with a digital
693 stadiometer to calculate BMI. Bioelectric impedance analysis (Seca Medical Body Composition
694 Analyzer mBCA 525, Hamburg, Germany) was used to obtain body fat percentage; values were
695 divided by 21 for females and by 31 for males to adjust for sex.

696 *Questionnaires.* Participants completed the Vividness of Olfactory Imagery³⁰ and
697 Vividness of Visual Imagery¹⁷ Questionnaires (VOIQ/VVIQ) in which they imagined odors/visual
698 objects across 16 scenarios and rated the vividness of their mental imagery from one “perfectly
699 clear and as vivid as normal smell/vision” to five “no image at all – you only know you are
700 thinking of an odor/object.” Both inventories were reverse scored such that higher sums
701 reflected larger self-reported imagery ability. Participants also did a modified Vividness of Food
702 Imagery Questionnaire (VFIQ)²⁰ that was similar to the VOIQ but focused on the ability to
703 imagine external food odors (e.g., of cookies in the oven) and flavors in the mouth (e.g., of
704 eating cookies, which also rely on olfaction). Total weekly metabolic equivalent task-minutes
705 (MET-minutes) from the International Physical Activity Questionnaire (IPAQ)¹³¹ and total score
706 from an American version of the Dietary Fat and Free Sugar Short Questionnaire (DFS)¹¹⁸ were
707 also used to assess habitual exercise and high-fat/high-carbohydrate intake, respectively. MET-
708 minutes for each type of physical activity represent the total minutes dedicated to the activity
709 times the estimated energy expenditure during the activity as a multiple of resting energy
710 expenditure (e.g., vigorous activities count toward a higher MET score than moderate activities).

711 *Perceptual Task of Odor Imagery Ability.* Detection thresholds for the rose and cookie
712 odors were first determined using a 16-step dilution series (4% odor by volume to 1.22ppm) in a
713 2-alternative forced-choice staircase procedure¹³². In a within-subjects and counterbalanced
714 design, participants then completed three imagery conditions (odor, visual, and none) of a
715 validated perceptual task²¹. During odor and visual imagery, they were instructed to imagine the
716 smell or sight of one odor type (e.g., rose) while trying to determine which of two samples
717 “smelled stronger.” In matched trials, the two samples contained: (1) the same odor as the
718 imagined type – e.g., rose – at their detection threshold level, and (2) the odorless propylene
719 glycol diluent. In mismatched trials, the two samples were: (1) the incongruent odor – e.g.,
720 cookie, and (2) the odorless diluent. In the no imagery condition, odor detection trials were
721 performed in the absence of imagery. The odor and visual imagery conditions contained 25
722 matched and 25 mismatched trials per odor (100 total), and the no imagery condition consisted
723 of 25 trials per odor (50 total), all counterbalanced for presentation order (i.e., sample one
724 contained the odor in 50% of trials). The interference effect (perceptual measure of odor
725 imagery ability) was calculated by subtracting detection accuracy (% trials correct) in
726 mismatched trials from that in matched trials of the odor imagery condition.

727 *Food Cue Reactivity.* Cue-induced craving strength was rated in response to 90
728 palatable food pictures³¹ on a horizontal VAS from “I do not want it at all” to “I crave it more than

729 anything,” and the average was calculated. Items included familiar American snacks and meals,
730 such as pizza and doughnuts. For cue-potentiated intake, participants completed a bogus taste
731 test³² in which they were instructed to eat as much as they liked while comparing the sensory
732 properties of two plates of cookies (e.g., which tastes sweeter/saltier, is fresher, or has better
733 quality chocolate). They were not explicitly told that the cookies were identical and that the
734 primary aim was to quantify the grams consumed. Data from two participants were excluded
735 from this measure after eating more than 3 SD above the group mean. Following the food
736 craving and intake paradigms, participants also rated their liking on the LHS³³ and frequency of
737 consumption in a typical month on a VAS (labels: 1 or less/month, 2/month, 3/month, 1/week,
738 2/week, 3–4/week, 5–6/week, 1/day, 2 or more/day) for each stimulus.

739

740 fMRI Session

741 Participants underwent fMRI scanning while performing a task in an event-related design
742 with six trial types: smell rose, cookie, or clean air; and imagine rose, cookie, or clean air. Each
743 trial began with a 5s auditory cue of “smell” or “imagine” followed by the name of the odor (e.g.,
744 “rose”) and the countdown “three, two, one, sniff.” Odor/clean air delivery (3s) was time-locked
745 to sniff onset. Trials were separated by intertrial intervals of 7–17s (mean = 10s). Participants
746 completed 30 trials per run (five of each type) and five runs per scan. Runs were ~9min long
747 and separated by ~2min breaks to minimize olfactory habituation.

748 Stimuli were delivered at concentrations matching individual ratings of moderate
749 intensity on the gLMS with a custom MRI-compatible olfactometer that has been described in
750 detail previously¹³³. In brief, the odors and clean air were presented via tubing channels and
751 removed by a vacuum line connected to a NuancePro Gel Nasal Pillow Fit-Pack Model
752 #1105167 nasal mask (Philips Respironics, Murrysville, PA, USA) worn by the subject. This
753 mask was coupled to an anti-viral filter (item #28350, Vitalograph, Lenexa, KS, USA) followed
754 by a pneumotachograph to measure airflow in the nose, which was then attached to a
755 spirometer and amplified with PowerLab 4SP for digital recording at 100 Hz in LabChart version
756 7 (ADInstruments, Sydney, Australia). Participants completed pre- and post-scan odor and
757 internal state ratings in the MRI bore before and after scanning. These ratings were averaged
758 and the differences of cookie versus rose intensity, familiarity, liking, and edibility were
759 quantified (Extended Data Fig. 4).

760 fMRI data were acquired with a Siemens 3 Tesla Magnetom Prisma scanner using a 32-
761 channel head coil. Images were collected at an angle of 30° off AC-PC to reduce susceptibility

762 artifacts in olfactory regions. Sagittal T1 anatomical images (repetition time TR = 1900ms, echo
763 time TE = 2.52ms, 176 slices, field of view FOV = 250mm, voxel size = 1×1×1mm) and
764 functional echo-planar images (EPIs) with a multiband BOLD sequence (TR = 2100ms, TE =
765 40ms, 72 slices, flip angle = 85°, FOV = 192mm, voxel size = 1.5×1.5×1.5mm) were obtained.

766

767 Follow-Up Session

768 All but one participant returned to the lab approximately one year later (days elapsed
769 from first to last session: M = 363.17, SD = 7.33, range = 340 – 378) to repeat the adiposity,
770 questionnaire, and food cue reactivity measures. Follow-up data from one participant was
771 excluded after they began a strict diet and lost more than 3 SD above the group mean in weight
772 change from the baseline to follow-up sessions.

773

774 **Data Analyses**

775 Behavioral Analyses

776 Pearson correlations, linear regressions, linear mixed effects models, ANOVAs, and
777 Student's t-tests were performed in MATLAB 2020a (Mathworks, Natick, Massachusetts, USA).
778 Data were plotted in Prism version 9.4.1 (GraphPad Software, San Diego, CA, USA). Mediation
779 and moderated mediation models were tested with bootstrapping (10000 samples, 95% CIs)
780 using the "PROCESS" macro version 4.1¹³⁴ models 4 and 7 implemented in SPSS Statistics
781 version 28 (IBM, Chicago, IL, USA). Significant effects were supported by confidence intervals
782 (CIs) excluding zero within the lower and upper bounds. For test-retest reliability, intraclass
783 correlation coefficient estimates and 95% CIs were calculated in SPSS based on single
784 measure, absolute agreement, 2-way mixed models. All measures showed moderate to good
785 reliability (Supplementary Table 9).

786 *Sniff Analyses.* The spirometer data were preprocessed and analyzed in MATLAB
787 R2020a. The raw airflow traces were separated by scan run and preprocessed (temporally
788 smoothed with a 500ms moving window, high-pass filtered at a cutoff of 0.02 Hz, and
789 normalized by subtracting the mean and dividing by the SD). Sniff onset for each trial was
790 determined by finding the time of the minimum signal value within a window of ± 0.75 s from the
791 auditory cue end. The time (latency) and value (amplitude) of the proximal maximum signal
792 were identified. Sniff offset was defined as the time (duration) at which the signal returned to its
793 original minimum, which was used in quantifying the area under the curve with the trapezoidal

794 method (volume). Finally, peak and mean airflow rates were assessed using derivatives at each
795 signal point indicating the instantaneous rates of change. These parameters were averaged by
796 trial type (e.g., smell rose) for each participant prior to comparison in ANOVAs (Extended Data
797 Fig. 5 and Supplementary Table 2).

798

799 fMRI Analyses

800 *Preprocessing.* The fMRI data were preprocessed and analyzed using FSL version
801 5.0.10 (FMRIB Software Library, Oxford, UK; Jenkinson et al., 2012) and SPM12 (Statistical
802 Parametric Mapping, Wellcome Centre for Human Neuroimaging, London, UK) implemented in
803 MATLAB R2019b. Functional EPIs were realigned to the mean and unwarped using fieldmaps,
804 slice-time corrected, and motion-corrected with the FSL tool MCFLIRT¹³⁶. The anatomical T1
805 image was coregistered to the mean EPI and spatially normalized to the standard MNI
806 reference with unified segmentation in SPM12. Prior to the univariate analyses, the resulting
807 deformation fields were applied to the EPI images, which were then smoothed with a 3mm full-
808 width-half-maximum Gaussian kernel.

809 *First Level Models.* General linear models (GLMs) were estimated for each participant
810 and run, separately for the normalized and smoothed EPI data (for univariate analyses) and the
811 non-normalized and non-smoothed EPI data (for decoding analyses). In each, the 6 trial types
812 (smell rose/cookie/clean air and imagine rose/cookie/clean air) were modeled with a canonical
813 hemodynamic response function as events of interest with onsets time-locked to the start of
814 odor/clean air delivery and durations of 3s. The following nuisance regressors were also
815 included: 24 motion parameters (the six SPM realignment parameters for the current volume,
816 six for the preceding volume, plus each of these values squared¹³⁷, the mean signal extracted
817 from the ventricular cerebrospinal fluid computed with *fslmeans*, a matrix of motion-outlier
818 volumes identified using *fsl_motion_outliers* (threshold = 75th percentile plus 2.5 times the
819 interquartile range and/or greater than 1mm of framewise displacement¹³⁸), and the
820 preprocessed sniff trace down-sampled to the scanner temporal resolution with decimation. A
821 128s high-pass filter was applied to remove low-frequency noise and slow signal drifts.

822 *Univariate Analyses.* The following contrast images were created at the single-subject
823 level and averaged across the five runs: smell odor (rose + cookie) > smell clean air, imagine
824 odor > imagine clean air, imagine odor > smell clean air, smell odor > imagine odor, and
825 imagine odor > smell odor. Group-level random effects analyses were conducted with one-

826 sample t-tests thresholded at $p_{\text{uncorrected}} < 0.001$ and a cluster size of at least five contiguous
827 voxels. Effects were considered significant at $p < 0.05$, cluster-level family-wise error corrected
828 across the whole brain. We also regressed the perceptual measure of odor imagery ability (i.e.,
829 the interference effect) against whole-brain BOLD responses to imagining odors > imagining
830 clean air and imagining odors > smelling clean air. Here we considered whole-brain effects and
831 those significant in the piriform cortex at a peak-level of $p < 0.025$, family-wise error small-
832 volume corrected for multiple comparisons in our two regions of interest (see below) and
833 subsequently Bonferroni corrected for the two SVC searches. The anatomical labels were
834 determined jointly from the “Atlas of the Human Brain”¹³⁹, an adult maximum probability atlas
835 prepared with SPM12 (www.brain-development.org)^{140–142}, and the Automated Anatomical
836 Labeling Atlas 3¹⁴³.

837 *Decoding Analyses.* The ROIs for the decoding analyses included the left and right
838 piriform cortices independently created from the Neurosynth¹⁴⁴ meta-analytic functional map for
839 the term “olfactory” (74 studies with 2021 activations, downloaded 9/15/2021). Activations from
840 this map were restricted to a threshold of $z = 6$ to ensure separability of the piriform clusters
841 from other nearby regions (e.g., the insula). The ROIs were converted from MNI space to each
842 subject’s native EPI space (voxel size = $1.5 \times 1.5 \times 1.5$ mm), resulting in clusters of 190 and 111
843 voxels for the left and right piriform, respectively.

844 MVPA was performed using The Decoding Toolbox¹⁴⁵ implemented in SPM12. For the
845 first decoding method (SVM classification), separate voxel-wise patterns were created for
846 smelling and imagining the rose and cookie odors by extracting the parameter estimates from
847 the first level GLMs and subtracting the mean activity across the conditions in each run. Feature
848 selection was used to identify the top class-discriminative voxels in each ROI with an ANOVA,
849 restricted to the number of voxels in each ROI maximally available for all subjects. An SVM from
850 the Library for Support Vector Machines (LIBSVM) package¹⁴⁶ was trained to decode rose
851 versus cookie using patterns of BOLD activation for smelling the odors in four of five scan runs.
852 The SVM was then tested for its accuracy to predict these odor categories from the patterns in
853 the left-out run. These steps were repeated for training and tested on the imagined odor
854 patterns, and for training on smelled and testing on imagined (and vice versa, averaged for the
855 crossmodal condition). SVM accuracies were compared to chance (50%) in one-sample t-tests
856 to assess group-level significance. SVM accuracies for the decoding of real odors in the left
857 versus right piriform cortex were also directly compared with a paired-samples t-test to assess
858 the laterality of the effect.

859 For the second decoding method (split-half voxel correlations), the first BOLD run was
860 treated as an odor localizer, which resulted in an equivalent number of even and odd runs
861 remaining for decoding (2 each). The voxels for each subject and ROI were functionally ranked
862 according to their t values in the contrast of smelling odor > smelling clean air from the localizer.
863 Again, the N-most odor-active voxels maximally available for all subjects were selected. The
864 split-half voxel correlations were then analyzed for the within-odor (e.g., smelling rose in even
865 runs versus smelling rose in odd runs) minus the between-odor (e.g., smelling rose in even runs
866 versus smelling cookie in odd runs) fMRI patterns in each ROI. In line with our SVM analyses,
867 we performed separate tests for real, imagined, and crossmodal odors. The resulting correlation
868 values were Fisher's Z transformed and compared to zero in one-sample t-tests to assess
869 group-level significance. They were also tested in correlations against the perceptual and self-
870 report measures of odor imagery ability. The latter analyses were performed in all individuals (n
871 = 44) and separately restricted to those with discriminable neural patterns for actual odors,
872 defined as within-odor minus between-odor voxel correlation Z-values > 0 (n = 30).

873 *Testing the Neurobiological Craving Signature.* The NCS is a recently developed
874 neuromarker or brain signature³⁴ of craving²⁹ that predicts the intensity of drug and food craving
875 with good accuracy. To assess the responses of the NCS-food pattern (a pattern that was
876 trained on visual food cues only), we computed the matrix dot product between this NCS-food
877 weight map and each participant's L2-normed contrast images for the six conditions: smell
878 cookie/rose/clean air and imagine cookie/rose/clean air. The matrix dot product provides one
879 scalar value (a 'pattern response' value) per participant and contrast image that describes the
880 similarity of the image to the weight map and the predicted level of food craving. Greater
881 responses of the NCS-food weight map indicate greater similarity to the craving map and higher
882 predicted levels of food craving. Pattern response values were statistically compared with an
883 ANOVA and paired t-tests for planned comparisons. All weight maps and code to apply the NCS
884 are publicly available at:
885 https://github.com/canlab/Neuroimaging_Pattern_Masks/tree/master/Multivariate_signature_patterns/2022_Koban_NCS_Craving.

887

888 **DATA AVAILABILITY**

889 The raw MRI data and sniff airflow traces can be downloaded from the OpenNEURO repository
890 under accession number ds004327: <https://openneuro.org/datasets/ds004327>. Statistical maps
891 of the human brain will be made available on the NeuroVault repository.

892

893 **ACKNOWLEDGEMENTS**

894 This work was supported by the National Science Foundation Graduate Research Fellowship
895 under Grant No. 2139841 (E.E.P.), the National Institute of Diabetes and Digestive and Kidney
896 Diseases of the National Institutes of Health under Award No. F31DK130556 (E.E.P.), and the
897 Modern Diet and Physiology Research Center (D.M.S.). The content is solely the responsibility
898 of the authors and does not necessarily represent the official views of the National Science
899 Foundation or the National Institutes of Health. We would like to thank Jason Avery for advice
900 on the fMRI decoding methods; Bojana Kuzmanovic for guidance on the fMRI preprocessing
901 pipeline; James Howard for example code to perform the sniffing analyses; Thomas Hummel,
902 Johan Lundström, Joel Mainland, and Paul Wise for their thoughts in troubleshooting the odor
903 detection threshold testing; Alain Dagher, Ralph DiLeone, and Barry Green for their helpful
904 suggestions to the project design; and Karen Martin for MR technical assistance.

905

906 **AUTHOR CONTRIBUTIONS**

907 Conceptualization, E.E.P. and D.M.S.; Methodology, E.E.P., X.S.D., J.D., M.J-G., J.T., Z.H.,
908 M.G.V., H.K., and D.M.S.; Formal Analysis, E.E.P., X.S.D., and L.K.; Investigation, E.E.P. and
909 J.T.; Resources, X.S.D., J.D., M.J-G., Z.H., M.G.V., T.W., H.K., and D.M.S.; Data Curation,
910 E.E.P.; Writing – Original Draft, E.E.P. and D.M.S.; Writing – Review & Editing, X.S.D., J.D.,
911 M.J-G., J.T., Z.H., M.G.V., L.K., T.W., and H.K.; Visualization, E.E.P.; Supervision, X.S.D., H.K.,
912 and D.M.S.; Funding Acquisition, E.E.P. and D.M.S.

913

914 **DECLARATION OF INTERESTS**

915 The authors declare no competing interests.

916 **REFERENCES**

- 917 1. Swinburn, B. A. *et al.* The global obesity pandemic: shaped by global drivers and local
918 environments. *The Lancet* **378**, 804–814 (2011).
- 919 2. Jansen, A. A learning model of binge eating: Cue reactivity and cue exposure. *Behaviour*
920 *Research and Therapy* **36**, 257–272 (1998).
- 921 3. Jansen, A., Havermans, R. C. & Nederkoorn, C. Cued Overeating. in *Handbook of*
922 *Behavior, Food and Nutrition* (eds. Preedy, V. R., Watson, R. R. & Martin, C. R.) 1431–
923 1443 (Springer, 2011). doi:10.1007/978-0-387-92271-3_92.
- 924 4. Hendrikse, J. J. *et al.* Attentional biases for food cues in overweight and individuals with
925 obesity: a systematic review of the literature. *Obesity Reviews* **16**, 424–432 (2015).
- 926 5. Boswell, R. G. & Kober, H. Food cue reactivity and craving predict eating and weight gain:
927 a meta-analytic review. *Obes Rev* **17**, 159–177 (2016).
- 928 6. Kavanagh, D. J., Andrade, J. & May, J. Imaginary Relish and Exquisite Torture: The
929 Elaborated Intrusion Theory of Desire. *Psychological Review* **112**, 446–467 (2005).
- 930 7. Croijmans, I. & Wang, Q. J. Do you want a description with that wine? The role of wine
931 mental imagery in consumer’s desire to drink using the revised Vividness of Wine Imagery
932 Questionnaire (VWIQ-II). *Journal of Sensory Studies* **37**, e12712 (2022).
- 933 8. Harvey, K., Kemps, E. & Tiggemann, M. The nature of imagery processes underlying food
934 cravings. *British Journal of Health Psychology* **10**, 49–56 (2005).
- 935 9. Kavanagh, D. J., May, J. & Andrade, J. Tests of the elaborated intrusion theory of craving
936 and desire: Features of alcohol craving during treatment for an alcohol disorder. *British*
937 *Journal of Clinical Psychology* **48**, 241–254 (2009).
- 938 10. May, J., Andrade, J., Panabokke, N. & Kavanagh, D. Images of desire: Cognitive models
939 of craving. *Memory* **12**, 447–461 (2004).
- 940 11. May, J., Andrade, J., Kavanagh, D. & Penfound, L. Imagery and strength of craving for
941 eating, drinking, and playing sport. *Cognition and Emotion* **22**, 633–650 (2008).
- 942 12. Statham, D. J. *et al.* Measuring alcohol craving: development of the Alcohol Craving
943 Experience questionnaire. *Addiction* **106**, 1230–1238 (2011).
- 944 13. Tiggemann, M. & Kemps, E. The phenomenology of food cravings: The role of mental
945 imagery. *Appetite* **45**, 305–313 (2005).
- 946 14. Pelchat, M. L., Johnson, A., Chan, R., Valdez, J. & Ragland, J. D. Images of desire: food-
947 craving activation during fMRI. *NeuroImage* **23**, 1486–1493 (2004).
- 948 15. Andrade, J., May, J., Deeprose, C., Baugh, S.-J. & Ganis, G. Assessing vividness of
949 mental imagery: The Plymouth Sensory Imagery Questionnaire. *British Journal of*
950 *Psychology* **105**, 547–563 (2014).
- 951 16. Bensafi, M. & Rouby, C. Individual Differences in Odor Imaging Ability Reflect Differences
952 in Olfactory and Emotional Perception. *Chem Senses* **32**, 237–244 (2007).
- 953 17. Marks, D. F. Visual Imagery Differences in the Recall of Pictures. *British Journal of*
954 *Psychology* **64**, 17–24 (1973).
- 955 18. Schifferstein, H. N. J. Comparing Mental Imagery across the Sensory Modalities.
956 *Imagination, Cognition and Personality* **28**, 371–388 (2009).

- 957 19. White, K. D., Ashton, R. & Brown, R. M. D. The measurement of imagery vividness:
958 Normative data and their relationship to sex, age, and modality differences. *British Journal*
959 *of Psychology* **68**, 203–211 (1977).
- 960 20. Patel, B. P., Aschenbrenner, K., Shamah, D. & Small, D. M. Greater perceived ability to
961 form vivid mental images in individuals with high compared to low BMI. *Appetite* **91**, 185–
962 189 (2015).
- 963 21. Djordjevic, J., Zatorre, R. J., Petrides, M. & Jones-Gotman, M. The Mind’s Nose: Effects of
964 Odor and Visual Imagery on Odor Detection. *Psychol Sci* **15**, 143–148 (2004).
- 965 22. Djordjevic, J., Zatorre, R. J., Petrides, M., Boyle, J. A. & Jones-Gotman, M. Functional
966 neuroimaging of odor imagery. *NeuroImage* **24**, 791–801 (2005).
- 967 23. Gottfried, J. A., Deichmann, R., Winston, J. S. & Dolan, R. J. Functional Heterogeneity in
968 Human Olfactory Cortex: An Event-Related Functional Magnetic Resonance Imaging
969 Study. *J. Neurosci.* **22**, 10819–10828 (2002).
- 970 24. Kent, C. & Lamberts, K. The encoding–retrieval relationship: retrieval as mental simulation.
971 *Trends in Cognitive Sciences* **12**, 92–98 (2008).
- 972 25. Poo, C. & Isaacson, J. S. Odor Representations in Olfactory Cortex: “Sparse” Coding,
973 Global Inhibition, and Oscillations. *Neuron* **62**, 850–861 (2009).
- 974 26. Rennaker, R. L., Chen, C.-F. F., Ruyle, A. M., Sloan, A. M. & Wilson, D. A. Spatial and
975 Temporal Distribution of Odorant-Evoked Activity in the Piriform Cortex. *J. Neurosci.* **27**,
976 1534–1542 (2007).
- 977 27. Stettler, D. D. & Axel, R. Representations of Odor in the Piriform Cortex. *Neuron* **63**, 854–
978 864 (2009).
- 979 28. Howard, J. D., Plailly, J., Grueschow, M., Haynes, J.-D. & Gottfried, J. A. Odor quality
980 coding and categorization in human posterior piriform cortex. *Nature Neuroscience* **12**,
981 932–938 (2009).
- 982 29. Koban, L., Wager, T. D. & Kober, H. A neuromarker for drug and food craving
983 distinguishes drug users from non-users. *Nat Neurosci* 1–10 (2022) doi:10.1038/s41593-
984 022-01228-w.
- 985 30. Gilbert, A., Voss, M. & Kroll, J. Vividness of olfactory mental imagery: correlations with
986 sensory response and consumer behavior. *Chem Senses* **22**, 686 (1997).
- 987 31. Boswell, R. G., Sun, W., Suzuki, S. & Kober, H. Training in cognitive strategies reduces
988 eating and improves food choice. *PNAS* **115**, E11238–E11247 (2018).
- 989 32. Robinson, E. *et al.* The bogus taste test: Validity as a measure of laboratory food intake.
990 *Appetite* **116**, 223–231 (2017).
- 991 33. Lim, J., Wood, A. & Green, B. G. Derivation and Evaluation of a Labeled Hedonic Scale.
992 *Chem Senses* **34**, 739–751 (2009).
- 993 34. Kragel, P. A., Koban, L., Barrett, L. F. & Wager, T. D. Representation, Pattern Information,
994 and Brain Signatures: From Neurons to Neuroimaging. *Neuron* **99**, 257–273 (2018).
- 995 35. Amedi, A., Malach, R. & Pascual-Leone, A. Negative BOLD Differentiates Visual Imagery
996 and Perception. *Neuron* **48**, 859–872 (2005).
- 997 36. Bunzeck, N., Wuestenberg, T., Lutz, K., Heinze, H.-J. & Jancke, L. Scanning silence:
998 Mental imagery of complex sounds. *NeuroImage* **26**, 1119–1127 (2005).

- 999 37. Cui, X., Jeter, C. B., Yang, D., Montague, P. R. & Eagleman, D. M. Vividness of mental
1000 imagery: Individual variability can be measured objectively. *Vision Research* **47**, 474–478
1001 (2007).
- 1002 38. Kikuchi, S., Kubota, F., Nisijima, K., Washiya, S. & Kato, S. Cerebral activation focusing on
1003 strong tasting food: a functional magnetic resonance imaging study. *NeuroReport* **16**, 281–
1004 283 (2005).
- 1005 39. Kobayashi, M. *et al.* Functional imaging of gustatory perception and imagery: “top-down”
1006 processing of gustatory signals. *NeuroImage* **23**, 1271–1282 (2004).
- 1007 40. Kosslyn, S. M., Thompson, W. L., Klm, I. J. & Alpert, N. M. Topographical representations
1008 of mental images in primary visual cortex. *Nature* **378**, 496–498 (1995).
- 1009 41. Schmidt, T. T. & Blankenburg, F. The Somatotopy of Mental Tactile Imagery. *Frontiers in*
1010 *Human Neuroscience* **13**, (2019).
- 1011 42. Yoo, S.-S., Freeman, D. K., McCarthy, J. J. I. & Jolesz, F. A. Neural substrates of tactile
1012 imagery: a functional MRI study. *NeuroReport* **14**, 581–585 (2003).
- 1013 43. Moulton, S. T. & Kosslyn, S. M. Imagining predictions: mental imagery as mental
1014 emulation. *Philosophical Transactions of the Royal Society B: Biological Sciences* **364**,
1015 1273–1280 (2009).
- 1016 44. de Araujo, I. E., Schatzker, M. & Small, D. M. Rethinking Food Reward. *Annual Review of*
1017 *Psychology* **71**, 139–164 (2020).
- 1018 45. Tsuneki, H. *et al.* Food odor perception promotes systemic lipid utilization. *Nat Metab* **4**,
1019 1514–1531 (2022).
- 1020 46. Zatorre, R. J., Jones-Gotman, M., Evans, A. C. & Meyer, E. Functional localization and
1021 lateralization of human olfactory cortex. *Nature* **360**, 339–340 (1992).
- 1022 47. Zatorre, R. J. & Jones-Gotman, M. Human olfactory discrimination after unilateral frontal or
1023 temporal lobectomy. *Brain* **114A**, 71–84 (1991).
- 1024 48. Jones-Gotman, M. & Zatorre, R. J. Odor Recognition Memory in Humans: Role of Right
1025 Temporal and Orbitofrontal Regions. *Brain and Cognition* **22**, 182–198 (1993).
- 1026 49. Carroll, B., Richardson, J. T. E. & Thompson, P. Olfactory Information Processing and
1027 Temporal Lobe Epilepsy. *Brain and Cognition* **22**, 230–243 (1993).
- 1028 50. Abraham, A. & Mathai, K. V. The effect of right temporal lobe lesions on matching of
1029 smells. *Neuropsychologia* **21**, 277–281 (1983).
- 1030 51. Bhutani, S. *et al.* Olfactory connectivity mediates sleep-dependent food choices in humans.
1031 *eLife* **8**, (2019).
- 1032 52. Howard, J. D. & Kahnt, T. Identity-Specific Reward Representations in Orbitofrontal Cortex
1033 Are Modulated by Selective Devaluation. *J. Neurosci.* **37**, 2627–2638 (2017).
- 1034 53. Gottfried, J. A., Winston, J. S. & Dolan, R. J. Dissociable Codes of Odor Quality and
1035 Odorant Structure in Human Piriform Cortex. *Neuron* **49**, 467–479 (2006).
- 1036 54. Steel, A., Billings, M. M., Silson, E. H. & Robertson, C. E. A network linking scene
1037 perception and spatial memory systems in posterior cerebral cortex. *Nat Commun* **12**,
1038 2632 (2021).
- 1039 55. Ganis, G., Thompson, W. L. & Kosslyn, S. M. Brain areas underlying visual mental imagery
1040 and visual perception: an fMRI study. *Cognitive Brain Research* **20**, 226–241 (2004).

- 1041 56. Bensafi, M., Sobel, N. & Khan, R. M. Hedonic-Specific Activity in Piriform Cortex During
1042 Odor Imagery Mimics That During Odor Perception. *Journal of Neurophysiology* **98**, 3254–
1043 3262 (2007).
- 1044 57. Levy, L. M., Henkin, R. I., Lin, C. S., Hutter, A. & Schellinger, D. Odor Memory Induces
1045 Brain Activation as Measured by Functional MRI. *Journal of Computer Assisted*
1046 *Tomography* **23**, 487 (1999).
- 1047 58. Royet, J.-P., Delon-Martin, C. & Plailly, J. Odor mental imagery in non-experts in odors: a
1048 paradox? *Frontiers in Human Neuroscience* **7**, (2013).
- 1049 59. Sobel, N. *et al.* Sniffing and smelling: separate subsystems in the human olfactory cortex.
1050 *Nature* **392**, 282–286 (1998).
- 1051 60. Arshamian, A., Olofsson, J. K., Jönsson, F. U. & Larsson, M. Sniff Your Way to Clarity: The
1052 Case of Olfactory Imagery. *Chem. Percept.* **1**, 242–246 (2008).
- 1053 61. Bensafi, M. *et al.* Olfactomotor activity during imagery mimics that during perception.
1054 *Nature Neuroscience* **6**, 1142–1144 (2003).
- 1055 62. Bensafi, M., Pouliot, S. & Sobel, N. Odorant-specific Patterns of Sniffing during Imagery
1056 Distinguish ‘Bad’ and ‘Good’ Olfactory Imagery. *Chemical Senses* **30**, 521–529 (2005).
- 1057 63. Veldhuizen, M. G. & Small, D. M. Modality-Specific Neural Effects of Selective Attention to
1058 Taste and Odor. *Chemical Senses* **36**, 747–760 (2011).
- 1059 64. Zelano, C. *et al.* Attentional modulation in human primary olfactory cortex. *Nat Neurosci* **8**,
1060 114–120 (2005).
- 1061 65. Gottfried, J. A., O’Doherty, J. & Dolan, R. J. Appetitive and Aversive Olfactory Learning in
1062 Humans Studied Using Event-Related Functional Magnetic Resonance Imaging. *J.*
1063 *Neurosci.* **22**, 10829–10837 (2002).
- 1064 66. Mandairon, N. *et al.* Context-driven activation of odor representations in the absence of
1065 olfactory stimuli in the olfactory bulb and piriform cortex. *Frontiers in Behavioral*
1066 *Neuroscience* **8**, (2014).
- 1067 67. Frankort, A. *et al.* Reward activity in satiated overweight women is decreased during
1068 unbiased viewing but increased when imagining taste: an event-related fMRI study. *Int J*
1069 *Obes (Lond)* **36**, 627–637 (2012).
- 1070 68. Han, P., Roitzsch, C., Horstmann, A., Pössel, M. & Hummel, T. Increased Brain Reward
1071 Responsivity to Food-Related Odors in Obesity. *Obesity* **29**, 1138–1145 (2021).
- 1072 69. Hubert, H. B., Fabsitz, R. R., Feinleib, M. & Brown, K. S. Olfactory sensitivity in humans:
1073 genetic versus environmental control. *Science* **208**, 607–609 (1980).
- 1074 70. Perszyk, E. E., Davis, X. S. & Small, D. M. Olfactory decoding is positively associated with
1075 ad libitum food intake in satiated humans. *Appetite* **180**, 106351 (2023).
- 1076 71. Riera, C. E. *et al.* The Sense of Smell Impacts Metabolic Health and Obesity. *Cell*
1077 *Metabolism* **26**, 198-211.e5 (2017).
- 1078 72. Schiffman, S. S. Sensory enhancement of foods for the elderly with monosodium
1079 glutamate and flavors. *Food Reviews International* **14**, 321–333 (1998).
- 1080 73. Stafford, L. D. & Whittle, A. Obese Individuals Have Higher Preference and Sensitivity to
1081 Odor of Chocolate. *Chem Senses* **40**, 279–284 (2015).

- 1082 74. Aschenbrenner, K. *et al.* The Influence of Olfactory Loss on Dietary Behaviors. *The*
1083 *Laryngoscope* **118**, 135–144 (2008).
- 1084 75. Han, P., Chen, H. & Hummel, T. Brain Responses to Food Odors Associated With BMI
1085 Change at 2-Year Follow-Up. *Frontiers in Human Neuroscience* **14**, 402 (2020).
- 1086 76. Mattes, R. D. *et al.* Dietary evaluation of patients with smell and/or taste disorders. *The*
1087 *American Journal of Clinical Nutrition* **51**, 233–240 (1990).
- 1088 77. Mattes, R. D. & Cowart, B. J. Dietary assessment of patients with chemosensory
1089 disorders. *Journal of the American Dietetic Association* **94**, 50–56 (1994).
- 1090 78. Patel, Z. M., DelGaudio, J. M. & Wise, S. K. Higher Body Mass Index Is Associated with
1091 Subjective Olfactory Dysfunction. *Behavioural Neurology* **2015**, e675635 (2015).
- 1092 79. Richardson, B. E., Vander Woude, E. A., Sudan, R., Thompson, J. S. & Leopold, D. A.
1093 Altered Olfactory Acuity in the Morbidly Obese. *OBES SURG* **14**, 967–969 (2004).
- 1094 80. Sun, X. *et al.* Basolateral Amygdala Response to Food Cues in the Absence of Hunger Is
1095 Associated with Weight Gain Susceptibility. *J. Neurosci.* **35**, 7964–7976 (2015).
- 1096 81. Temmel, A. F. P. *et al.* Characteristics of Olfactory Disorders in Relation to Major Causes
1097 of Olfactory Loss. *Archives of Otolaryngology–Head & Neck Surgery* **128**, 635–641 (2002).
- 1098 82. Boone, M. H., Liang-Guallpa, J. & Krashes, M. J. Examining the role of olfaction in dietary
1099 choice. *Cell Reports* **34**, 108755 (2021).
- 1100 83. Poessel, M. *et al.* Brain response to food odors is not associated with body mass index
1101 and obesity-related metabolic health measures. *Appetite* 105774 (2021)
1102 doi:10.1016/j.appet.2021.105774.
- 1103 84. Shepherd, G. M. Smell images and the flavour system in the human brain. *Nature* **444**,
1104 316–321 (2006).
- 1105 85. Cecchetto, C., Rumiati, R. I. & Aiello, M. Alexithymia and emotional reactions to odors. *Sci*
1106 *Rep* **7**, (2017).
- 1107 86. Mendelsohn, A., Pine, A. & Schiller, D. Between Thoughts and Actions: Motivationally
1108 Salient Cues Invigorate Mental Action in the Human Brain. *Neuron* **81**, 207–217 (2014).
- 1109 87. Nachev, P., Kennard, C. & Husain, M. Functional role of the supplementary and pre-
1110 supplementary motor areas. *Nat Rev Neurosci* **9**, 856–869 (2008).
- 1111 88. Tanji, J. New concepts of the supplementary motor area. *Current Opinion in Neurobiology*
1112 **6**, 782–787 (1996).
- 1113 89. Craig, A. D. How do you feel — now? The anterior insula and human awareness. *Nat Rev*
1114 *Neurosci* **10**, 59–70 (2009).
- 1115 90. Livneh, Y. & Andermann, M. L. Cellular activity in insular cortex across seconds to hours:
1116 Sensations and predictions of bodily states. *Neuron* **109**, 3576–3593 (2021).
- 1117 91. Naqvi, N. H. & Bechara, A. The hidden island of addiction: the insula. *Trends in*
1118 *Neurosciences* **32**, 56–67 (2009).
- 1119 92. Livneh, Y. *et al.* Estimation of Current and Future Physiological States in Insular Cortex.
1120 *Neuron* **105**, 1094-1111.e10 (2020).
- 1121 93. Kusumoto-Yoshida, I., Liu, H., Chen, B. T., Fontanini, A. & Bonci, A. Central role for the
1122 insular cortex in mediating conditioned responses to anticipatory cues. *Proceedings of the*
1123 *National Academy of Sciences* **112**, 1190–1195 (2015).

- 1124 94. Dijkstra, N., Bosch, S. E. & Gerven, M. A. J. van. Vividness of Visual Imagery Depends on
1125 the Neural Overlap with Perception in Visual Areas. *J. Neurosci.* **37**, 1367–1373 (2017).
- 1126 95. Formisano, E. *et al.* Tracking the Mind’s Image in the Brain I: Time-Resolved fMRI during
1127 Visuospatial Mental Imagery. *Neuron* **35**, 185–194 (2002).
- 1128 96. Ghaem, O. *et al.* Mental navigation along memorized routes activates the hippocampus,
1129 precuneus, and insula. *NeuroReport* **8**, 739–744 (1997).
- 1130 97. Halpern, A. R. Cerebral Substrates of Musical Imagery. *Annals of the New York Academy*
1131 *of Sciences* **930**, 179–192 (2001).
- 1132 98. Hoppe, J. M., Holmes, E. A. & Agren, T. Exploring the neural basis of fear produced by
1133 mental imagery: imaginal exposure in individuals fearful of spiders. *Philosophical*
1134 *Transactions of the Royal Society B: Biological Sciences* **376**, 20190690 (2021).
- 1135 99. Iseki, K., Hanakawa, T., Shinozaki, J., Nankaku, M. & Fukuyama, H. Neural mechanisms
1136 involved in mental imagery and observation of gait. *NeuroImage* **41**, 1021–1031 (2008).
- 1137 100. Jabbi, M., Bastiaansen, J. & Keysers, C. A Common Anterior Insula Representation of
1138 Disgust Observation, Experience and Imagination Shows Divergent Functional
1139 Connectivity Pathways. *PLOS ONE* **3**, e2939 (2008).
- 1140 101. Mcnorgan, C. A meta-analytic review of multisensory imagery identifies the neural
1141 correlates of modality-specific and modality-general imagery. *Frontiers in Human*
1142 *Neuroscience* **6**, (2012).
- 1143 102. Olivetti Belardinelli, M. *et al.* An fMRI investigation on image generation in different sensory
1144 modalities: The influence of vividness. *Acta Psychologica* **132**, 190–200 (2009).
- 1145 103. Zvyagintsev, M. *et al.* Brain networks underlying mental imagery of auditory and visual
1146 information. *European Journal of Neuroscience* **37**, 1421–1434 (2013).
- 1147 104. Abdolahi, A. *et al.* Damage to the insula leads to decreased nicotine withdrawal during
1148 abstinence. *Addiction* **110**, 1994–2003 (2015).
- 1149 105. Lin, X. *et al.* Neural substrates of smoking and reward cue reactivity in smokers: a meta-
1150 analysis of fMRI studies. *Transl Psychiatry* **10**, 1–9 (2020).
- 1151 106. Moran-Santa Maria, M. M. *et al.* Right anterior insula connectivity is important for cue-
1152 induced craving in nicotine-dependent smokers. *Addiction Biology* **20**, 407–414 (2015).
- 1153 107. Naqvi, N. H., Rudrauf, D., Damasio, H. & Bechara, A. Damage to the Insula Disrupts
1154 Addiction to Cigarette Smoking. *Science* **315**, 531–534 (2007).
- 1155 108. Smolka, M. N. *et al.* Severity of nicotine dependence modulates cue-induced brain activity
1156 in regions involved in motor preparation and imagery. *Psychopharmacology* **184**, 577–588
1157 (2006).
- 1158 109. Tang, D. W., Fellows, L. K., Small, D. M. & Dagher, A. Food and drug cues activate similar
1159 brain regions: A meta-analysis of functional MRI studies. *Physiology & Behavior* **106**, 317–
1160 324 (2012).
- 1161 110. Leclerc, M. P. *et al.* Externalization Errors of Olfactory Source Monitoring in Healthy
1162 Controls—An fMRI Study. *Chem Senses* **44**, 593–606 (2019).
- 1163 111. Smith, E., Hay, P., Campbell, L. & Trollor, J. N. A review of the association between
1164 obesity and cognitive function across the lifespan: implications for novel approaches to
1165 prevention and treatment. *Obesity Reviews* **12**, 740–755 (2011).

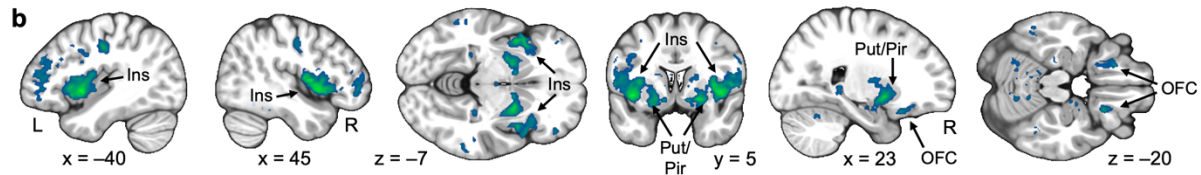
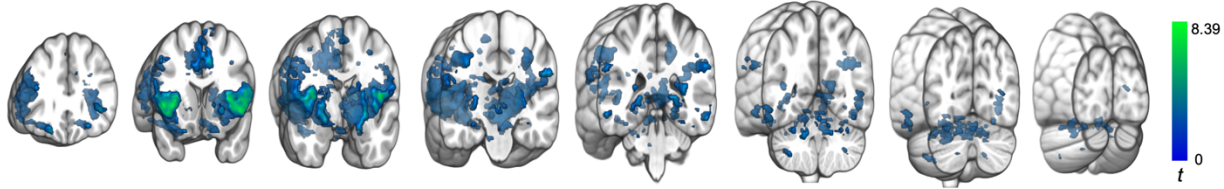
- 1166 112. Leng, X. *et al.* Episodic memory for food and non-food cues in females with obesity. *Eating*
1167 *Behaviors* **40**, 101472 (2021).
- 1168 113. Kanoski, S. E. & Davidson, T. L. Western diet consumption and cognitive impairment:
1169 Links to hippocampal dysfunction and obesity. *Physiology & Behavior* **103**, 59–68 (2011).
- 1170 114. Parent, M. B., Higgs, S., Cheke, L. G. & Kanoski, S. E. Memory and eating: A bidirectional
1171 relationship implicated in obesity. *Neuroscience & Biobehavioral Reviews* **132**, 110–129
1172 (2022).
- 1173 115. Bensafi, M. *et al.* Expertise shapes domain-specific functional cerebral asymmetry during
1174 mental imagery: the case of culinary arts and music. *European Journal of Neuroscience*
1175 **45**, 1524–1537 (2017).
- 1176 116. Plailly, J., Delon-Martin, C. & Royet, J.-P. Experience induces functional reorganization in
1177 brain regions involved in odor imagery in perfumers. *Human Brain Mapping* **33**, 224–234
1178 (2012).
- 1179 117. Croijmans, I., Speed, L. J., Arshamian, A. & Majid, A. Expertise Shapes Multimodal
1180 Imagery for Wine. *Cognitive Science* **44**, e12842 (2020).
- 1181 118. Francis, H. & Stevenson, R. Validity and test–retest reliability of a short dietary
1182 questionnaire to assess intake of saturated fat and free sugars: a preliminary study.
1183 *Journal of Human Nutrition and Dietetics* **26**, 234–242 (2013).
- 1184 119. Samson, L. & Buijzen, M. Craving healthy foods?! How sensory appeals increase
1185 appetitive motivational processing of healthy foods in adolescents. *Media Psychology* **23**,
1186 159–183 (2020).
- 1187 120. Schyns, G., van den Akker, K., Roefs, A., Houben, K. & Jansen, A. Exposure therapy vs
1188 lifestyle intervention to reduce food cue reactivity and binge eating in obesity: A pilot study.
1189 *Journal of Behavior Therapy and Experimental Psychiatry* **67**, 101453 (2020).
- 1190 121. Schyns, G., Roefs, A., Mulkens, S. & Jansen, A. Expectancy violation, reduction of food
1191 cue reactivity and less eating in the absence of hunger after one food cue exposure
1192 session for overweight and obese women. *Behaviour Research and Therapy* **76**, 57–64
1193 (2016).
- 1194 122. Andrade, J., May, J. & Kavanagh, D. Sensory Imagery in Craving: From Cognitive
1195 Psychology to New Treatments for Addiction. *Journal of Experimental Psychopathology* **3**,
1196 127–145 (2012).
- 1197 123. Andrade, J., Khalil, M., Dickson, J., May, J. & Kavanagh, D. J. Functional Imagery Training
1198 to reduce snacking: Testing a novel motivational intervention based on Elaborated
1199 Intrusion theory. *Appetite* **100**, 256–262 (2016).
- 1200 124. Kober, H. *et al.* Prefrontal–striatal pathway underlies cognitive regulation of craving. *PNAS*
1201 **107**, 14811–14816 (2010).
- 1202 125. Faul, F., Erdfelder, E., Lang, A.-G. & Buchner, A. G*Power 3: A flexible statistical power
1203 analysis program for the social, behavioral, and biomedical sciences. *Behavior Research*
1204 *Methods* **39**, 175–191 (2007).
- 1205 126. Faul, F., Erdfelder, E., Buchner, A. & Lang, A.-G. Statistical power analyses using
1206 G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*
1207 **41**, 1149–1160 (2009).

- 1208 127. Peirce, J. W. PsychoPy—Psychophysics software in Python. *Journal of Neuroscience*
1209 *Methods* **162**, 8–13 (2007).
- 1210 128. Bartoshuk, L. M. *et al.* Valid across-group comparisons with labeled scales: the gLMS
1211 versus magnitude matching. *Physiology & Behavior* **82**, 109–114 (2004).
- 1212 129. Green, B. G., Shaffer, G. S. & Gilmore, M. M. Derivation and evaluation of a semantic
1213 scale of oral sensation magnitude with apparent ratio properties. *Chemical Senses* **18**,
1214 683–702 (1993).
- 1215 130. Green, B. G. *et al.* Evaluating the ‘Labeled Magnitude Scale’ for Measuring Sensations of
1216 Taste and Smell. *Chemical Senses* **21**, 323–334 (1996).
- 1217 131. Hagströmer, M., Oja, P. & Sjöström, M. The International Physical Activity Questionnaire
1218 (IPAQ): a study of concurrent and construct validity. *Public Health Nutrition* **9**, 755–762
1219 (2006).
- 1220 132. Doty, R. L. Office Procedures for Quantitative Assessment of Olfactory Function. *American*
1221 *Journal of Rhinology* **21**, 460–473 (2007).
- 1222 133. Small, D. M., Veldhuizen, M. G., Felsted, J., Mak, Y. E. & McGlone, F. Separable
1223 Substrates for Anticipatory and Consummatory Food Chemosensation. *Neuron* **57**, 786–
1224 797 (2008).
- 1225 134. Hayes, A. F. *Introduction to Mediation, Moderation, and Conditional Process Analysis,*
1226 *Second Edition: A Regression-Based Approach.* (Guilford Publications, 2017).
- 1227 135. Jenkinson, M., Beckmann, C. F., Behrens, T. E. J., Woolrich, M. W. & Smith, S. M. FSL.
1228 *NeuroImage* **62**, 782–790 (2012).
- 1229 136. Jenkinson, M., Bannister, P., Brady, M. & Smith, S. Improved Optimization for the Robust
1230 and Accurate Linear Registration and Motion Correction of Brain Images. *NeuroImage* **17**,
1231 825–841 (2002).
- 1232 137. Friston, K. J., Williams, S., Howard, R., Frackowiak, R. S. J. & Turner, R. Movement-
1233 Related effects in fMRI time-series. *Magnetic Resonance in Medicine* **35**, 346–355 (1996).
- 1234 138. Power, J. D., Barnes, K. A., Snyder, A. Z., Schlaggar, B. L. & Petersen, S. E. Spurious but
1235 systematic correlations in functional connectivity MRI networks arise from subject motion.
1236 *NeuroImage* **59**, 2142–2154 (2012).
- 1237 139. Mai, J. K., Majtanik, M. & Paxinos, G. *Atlas of the Human Brain.* (Academic Press, 2015).
- 1238 140. Faillenot, I., Heckemann, R. A., Frot, M. & Hammers, A. Macroanatomy and 3D
1239 probabilistic atlas of the human insula. *NeuroImage* **150**, 88–98 (2017).
- 1240 141. Gousias, I. S. *et al.* Automatic segmentation of brain MRIs of 2-year-olds into 83 regions of
1241 interest. *NeuroImage* **40**, 672–684 (2008).
- 1242 142. Hammers, A. *et al.* Three-dimensional maximum probability atlas of the human brain, with
1243 particular reference to the temporal lobe. *Human Brain Mapping* **19**, 224–247 (2003).
- 1244 143. Rolls, E. T., Huang, C.-C., Lin, C.-P., Feng, J. & Joliot, M. Automated anatomical labelling
1245 atlas 3. *NeuroImage* **206**, 116189 (2020).
- 1246 144. Yarkoni, T., Poldrack, R. A., Nichols, T. E., Van Essen, D. C. & Wager, T. D. Large-scale
1247 automated synthesis of human functional neuroimaging data. *Nat Methods* **8**, 665–670
1248 (2011).

- 1249 145. Hebart, M. N., Görgen, K. & Haynes, J.-D. The Decoding Toolbox (TDT): a versatile
1250 software package for multivariate analyses of functional imaging data. *Front. Neuroinform.*
1251 **8**, (2015).
- 1252 146. Chang, C.-C. & Lin, C.-J. LIBSVM: A library for support vector machines. *ACM Trans.*
1253 *Intell. Syst. Technol.* **2**, 27:1-27:27 (2011).
1254

1255 **EXTENDED DATA FIGURES**

a Imagine odor > smell clean air



1256

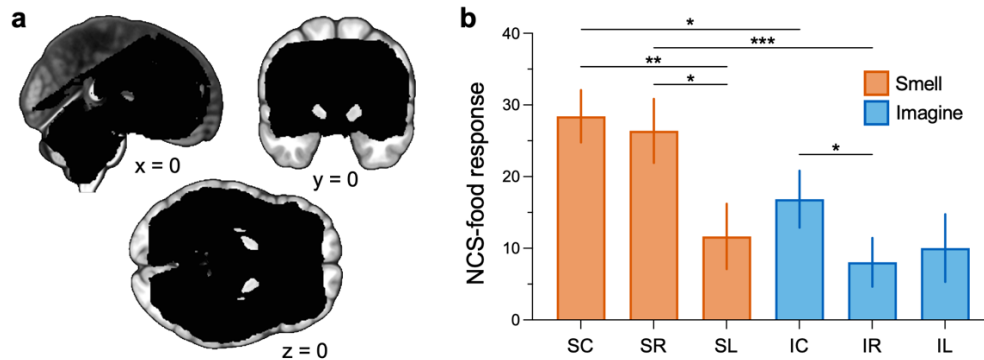
1257 **Extended Data Fig. 1: Univariate fMRI Activity to Imagining Odors > Smelling Clean Air**

1258 (a) 3D coronal sections (18mm thick) evenly spanning $y = 56$ to -88 mm depict significant BOLD responses to imagining odors >
 1259 smelling clean air in the bilateral insula, putamen extending into the piriform cortices, pallidum, and orbitofrontal, middle frontal, and
 1260 precentral gyri, among other regions.

1261 (b) Important areas of activation for imagining odors > smelling clean air are highlighted with custom coordinates (see
 1262 Supplementary Table 4).

1263 Brain sections show the SPM t -map ($p_{\text{uncorrected}} < 0.005$, clusters of at least 5 voxels) overlaid onto an anatomical template in MNI
 1264 coordinates for illustrative purposes. Color bars depict t values. L, left; R, right; Ins, insula; OFC, orbitofrontal cortex; Pir, piriform
 1265 cortex; Put, putamen.

1266



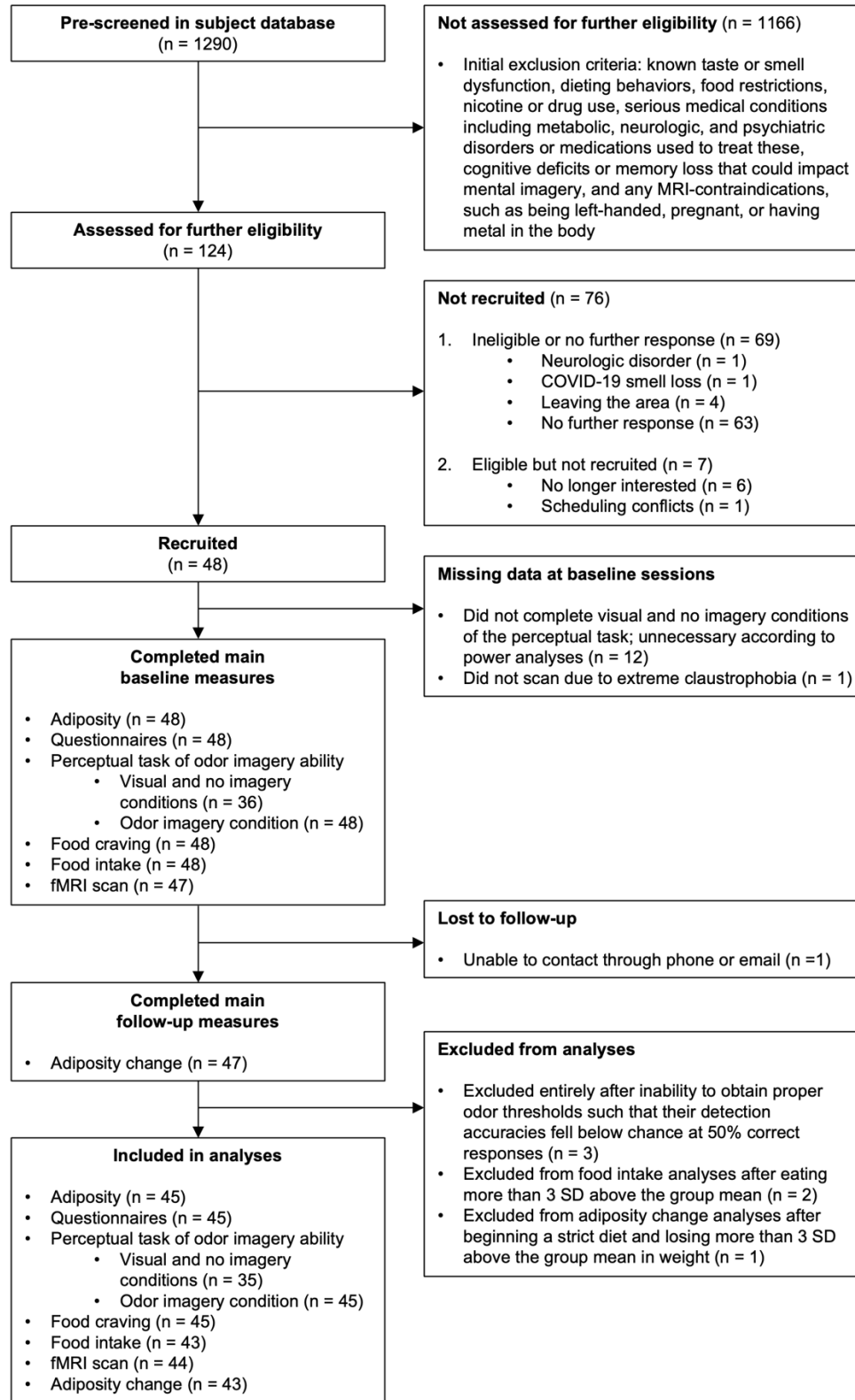
1267

1268 **Extended Data Fig. 2: Imagining a Food Odor Elicits Greater Neurobiological Craving Signature Activation**
 1269 **than Imagining a Nonfood Odor**

1270 (a) Mask constructed from the intersection of EPI scan windows for all participants (black) overlaid onto an anatomical template in
 1271 MNI coordinates to depict the fMRI signal coverage.

1272 (b) The effects of smelling and imagining cookie and rose odors and clean air on pattern responses of the recently developed
 1273 Neurobiological Craving Signature (NCS) from independent work²⁹.

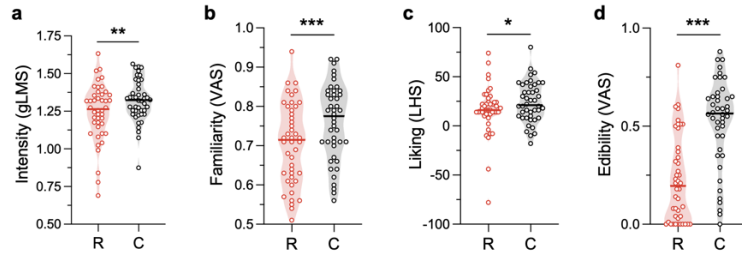
1274 S, smell; I, imagine; C, cookie; R, rose; L, clean air. Post-hoc comparisons: * $p < 0.01$, ** $p < 0.001$, *** $p < 0.0001$.



1275

1276 **Extended Data Fig. 3: Participant Flow Diagram**

1277 Flow diagram depicting the number of individuals at each stage of the study.

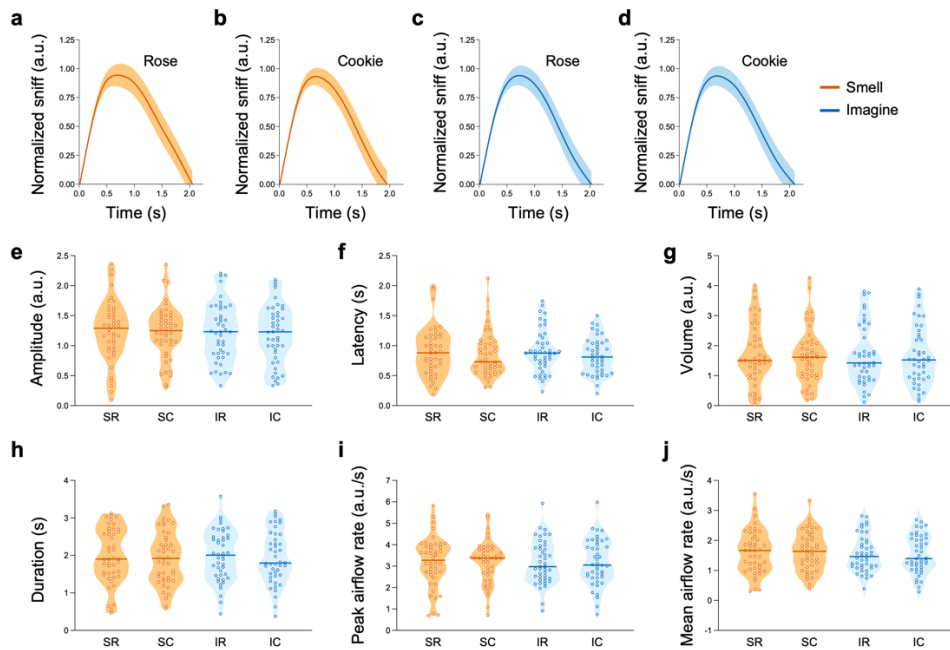


1278

1279 **Extended Data Fig. 4: Odor Rating Comparisons for Rose Versus Cookie**

1280 (a–d) The cookie odor was rated to be significantly more intense (a), familiar (b), liked (c), and edible (d) than the rose odor.
 1281 However, the cookie minus rose odor ratings were not correlated with any measure of odor imagery ability (Supplementary Table 1).
 1282 Truncated violin plots depict single participants with shading to represent the density of the points around the median line. R, rose;
 1283 C, cookie; gLMS, general Labeled Magnitude Scale^{128–130}; VAS, visual analog scale; LHS, Labeled Hedonic Scale³³. * $p < 0.05$; ** $p < 0.01$;
 1284 *** $p < 0.0001$.

1285



1286

1287 **Extended Data Fig. 5: Sniff Parameters for Smelling and Imagining the Rose and Cookie Odors**

1288 (a–d) Normalized sniff traces ($M \pm SEM$) for smelling the rose (a) and cookie (b) odors and imagining the rose (c) and cookie (d)
 1289 odors.
 1290 (e–j) Sniff amplitude (e), latency (f), volume (g), duration (h), peak airflow rate (i), and mean airflow rate (j) while smelling and
 1291 imagining the rose and cookie odors. Differences in the sniff parameters for imagining the cookie minus rose odor were not
 1292 correlated with any measure of odor imagery ability (Supplementary Table 1). ANOVAs also revealed no main effects or interactions
 1293 of modality (smell/imagine), odor (rose/cookie), or the perceptual measure of odor imagery ability (the interference effect) on any
 1294 sniff parameter (Supplementary Table 2).

1295 Truncated violin plots depict single participants with shading to represent the density of the points around the median line. S, smell;
 1296 I, imagine; R, rose; C, cookie; a.u., arbitrary units.