Understand human olfactory ecology and the methodological challenges in field-testing olfactory ability

Short Title: Olfactory ability in the field: methods and results

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ABSTRACT
We know little about human olfactory ability in natural settings—for humans, this includes both natural and built environments. Our knowledge derives from clinics and lab experiments using samples of convenience, often students and usually WEIRD. But, humans live in odor rich environments, most are not western, and many are not industrialized or formally educated. The problem is that we lack field methods for studying olfactory ability outside the lab and cannot fully understand olfaction within an ecological setting. To explore what clinical methods might be transferrable from the lab to the field, we completed three experiments in a variety of settings with and without repeated measures. Odor purity and background odors at test sites are not mitigated because the larger research question of interest is to understand the impact of varying test environments on olfactory ability—how our sense of smell operates in daily life. Results suggest that olfactory ability is much worse in non-lab settings than in the lab and that variation in testing due to the environment does not cause significantly different outcomes. Further, we find the that forced choice method for the short odor identification tests introduces a learning bias wherein participants tend to get better at naming odors in the first trial due to having seen 'correct' answers on the forced choice list. Challenges of studying human olfaction in non-lab settings include recruiting participants, minimizing test time, and avoiding subject learning. We report two broader implications of this research. First, comparing field-collected to lab-collected data is not meaningful for understanding human olfactory ecology. The fundamental differences in test conditions (pure single odors in an air-controlled lab versus odor mixtures with variable environmental conditions) preclude robust comparisons. While clinical diagnoses are essential to, in particular, geriatric health, they cannot inform an understanding olfactory performance in an evolutionarily salient way. Second, superior female olfactory ability appeared to be upheld in our field-based studies and we postulate that perhaps there is evolutionary explanation given that females produce most of the food in foraging societies and engage in human-environment interactions in such a way that forces them to learn odors rapidly. These data are the first to explore methods issues on testing olfactory ability in the field in an anthropologically and evolutionarily meaningful way.

KEYWORDS
Smelling in the wild, psychophysics, olfaction, human olfactory ecology, built environment

1 INTRODUCTION

We know little about how humans detect, discriminate, and identify odors in mixtures in natural settings—for humans, natural settings include the built environment, both urban and rural. The vast majority of our knowledge on human olfaction derives from psychology and cognitive science lab studies conducted in odor-controlled environments using samples of convenience—mostly WEIRD (Henrich et al., 2010) and often students (Hanel et al., 2016). Meanwhile, the vast majority of humans live in smelly environments with rich odor mixtures (naturally or artificially produced) and are non-western, many of which are not industrialized and do not have western-style education, the effect of which on non-western populations has been troubling (Eras, 2016).

The limited research done on olfactory ability in different ecological settings suggest that non-industrial populations may have a better sense of smell even if those studies compared field-based data to those from a lab (Sorokowska et al., 2014; Sorokowska et al., 2013). Further, the documented anthropogenic disruptions to sensory-guided non-human animal behavior indicates that industrialization challenges the senses (for example, see Boivin et al., 2016; Jürgens et al., 2017; Kunc et al., 2014; Morris-Drake et al., 2016). While there are minimal data on humans (Hoover, 2018a; Hoover, 2018b), there is an established relationship between modern living and diminished olfaction—pollution damages olfactory soft tissue and reduces olfactory acuity (for a review, see Ajmani et al., 2016). Olfactory ability is a critical component of mental health (for recent reviews, see Rochet et al., 2018; Taalman et al., 2017), appetite regulation (Boesveldt et al., 2017; Obrebowski et al., 2000; Ulusoy et al., 2016; van Langeveld et al., 2018), and sociability (Alves-Oliveira et al., 2017; Bendas et al., 2018; Croy et al., 2013; Lübke et al., 2015; Mutic et al., 2017; Mutic et al., 2015; Oettl et al., 2017; Oettl et al., 2016; Prehn-Kristensen et al., 2009; White et al., 2017; Zou et al., 2016). The principle challenge in generating olfactory ability data to capture the human condition broadly is the lack of field-based methods (Kern et al., 2014).

The majority of widely-used olfactory ability assessment tools rely partly on correct odor identification, which introduces a bias toward odor familiarity (to be identifiable, the odor must have been previously experienced), which is influenced by culture and geographic environment. Of the most widely-used olfactory ability assessment tools—Sniffin' Sticks Test (Kobal et al., 2000) and the University of Pennsylvania Smell Identification Test (Doty et al., 1984b)—the Sniffin' Sticks test (SST) alone mitigates familiarity bias by including two additional subsets: threshold detection and discrimination. A recently introduced set of tools, SMELL-R and Smell-S (Hsieh et al., 2017), does not rely on prior olfactory experience and avoids idiosyncratic odor-specific insensitivity by using odor mixes. While promising, they have not been widely validated for use in clinical settings, let alone the field. Currently, the best set of tools for field-testing would be the Sniffin' Sticks due to their portability, shelf-life, and assessment of three domains of olfactory function.

The Olfactory Function Field Exam (OFEE) is an 11-minute olfactory function test that uses a modified and abbreviated version of Sniffin' Sticks—two odors for threshold detection and five odors for odor identification (Kern et al., 2014). The OFFE was designed to capture olfactory function data in home environments, rather than the lab, which also widens the data collection demographically. As part of The National Social Life, Health, and Aging Project in the United

States, the OFFE was validated on a cohort of 2,304 older adults and conducted in participants' homes following a short odor training session. Results were nearly identical to testing conducted in labs on a similarly aged cohort (Kern et al., 2014)—these results suggest that between-subjects environmental variation (in private homes) did not contribute significantly to summary results. But, tests were conducted in home environments where participants are adapted to the smellscape of their own environment (Auffarth, 2013; Dalton, 2000). Will environmental variation in field studies be comparable to those in the lab when the field environment is not familiar?

Because we are interested in environmental variation contributions to olfactory ability scores as well as field-based methods development, we conducted three separate experiments in various field and lab locations in the London area. The first experiment, Market Smells 1 (MS1), examined olfactory ability in two open air market settings. The second experiment, Market Smells 2 (MS2), examined olfactory ability in three different open-air market settings on the same individuals in a repeated measures design. The third study, Market Smells 3 (MS3), examined olfactory ability in two different lab settings, one low odor and one experimentally simulated market environment.

2 MATERIALS

The Sniffin' Sticks used for MS1 were purchased one month prior to field work (September 2017). The Sniffin' Sticks used for MS2 were purchased one month prior to field work (July 2018). The Sniffin' Sticks used for odor identification in MS3 (February 2019) were the same as the ones used for MS2 and, at 7 months old, they are within manufacturers range of one year. Even so, prior testing on Sniffin' Sticks threshold test (n-butanol) has indicated that sticks can retain strength up to three years (Denzer et al., 2014). When not in use, Sniffin' Sticks were stored at the University of Roehampton at a temperature within the recommended range. Raw data are shared at figshare (DOI).

3 METHODS

All data were analyzed in R for Windows v3.5.3 (Charif et al., 2007) using the R Studio GUI v1.1.463 (RStudio Team, 2015). Graphs were created in ggplot2 (Wickham, 2016) and ggpubr (Kassambara, 2018). Specific statistical tests (and their R packages) are discussed below and in Results.

3.1 Data Collection Methods

We chose the abbreviated odor identification component of SST because it is the quickest to deliver and the most practical in a field setting where participants may not have more than 3-5 minutes of time to offer. We realize that odor identification is the most challenging of the three components, even when odor familiarity and odor terms have been validated, such as they have with our UK-based population (Neumann et al., 2012). In our experiments, issues of odor purity and background odors are not mitigated because the ultimate aim is to assess olfactory ability in daily life. Participants were screened via questionnaire for factors that might contribute to impaired olfaction (e.g., smoking, allergies). No participant had eaten or drunk anything other than water 20 minutes prior to testing. Testing protocols were the same for both tests: a tester wearing cotton gloves (and wearing no scented products) presented the odor underneath the nostrils of the participant for three seconds and asked if the participant could smell the odor, and,

if so, to describe it (free choice method). For the repeated measures test, we followed the free choice with a forced-choice method where participants were asked to choose from a card containing 20 odors (see Table 2 of Mueller et al., 2006).

3.2 Data Coding. All descriptive answers (whether free or forced choice) were coded as correct, near miss, far miss, and incorrect (Cain, 1979) by two observers (JCB, KCH). Inter-observer (JCB, KCH) code agreement was analyzed by Cohen's kappa (κ) using irr (Gamer et al., 2012) in the lpsolve package (Berkelaar, 2015).

3.3 Data Exploration. We explored data using FactoMineR (Le et al., 2008).

3.4 Descriptive Terms. Studies on odor-based language suggest that western populations have a limited number of words for abstract odor qualities (e.g., musty)—most terms for odors are source based. We were curious about how frequently abstract terms (even if limited in number) were used, even if in combination with a source term. In qualifying what constitutes an abstract term, we were liberal and included true abstract terms (e.g. pungent, musty), hedonic values (liking or not liking), and taste terms (e.g., sweet, savoury). We also looked at how often source terms named products (e.g., air freshener rather than lemon or rose, Vicks rather than menthol). We conducted a correspondence analysis on age and sex associations with the use abstract and product terms using FactoMineR (Le et al., 2008).

3. Methods Testing

Established lab-based odor identification protocols rely on a forced-choice method (Hummel et al., 2001; Hummel et al., 1997). We had some misgivings about using this in the field because the forced choice method engages volunteers in the process of elimination and possibly guesswork, possibly masking true olfactory ability (Kern et al., 2014). Indeed, lab studies show improved performance with verbal prompts compared to free description, which is meant to overcome the challenges of odor identification (Hummel et al., 2007; Negoias et al., 2010). We tested whether our results would reflect better performance when receiving a prompt (forced choice) using the La Place approximation in a GLMM with repeated measures (random factor=participant ID) using lme4 (Bates et al., 2015).

As noted previously, all distractors and five correct terms (for the 5-odor test) are placed on one card, exposing participants to correct answers following the first odor. We were concerned that the short 5-odor test and short gap between trials would introduce a learning bias from the forced-choice card. Thus, we collected only free choice data for MS1 but decided to collect both free and forced choice data for MS2 and MS3 to assess whether our concerns over test learning were valid. We only showed participants the card when prompting a forced-choice answer to minimize the learning impact. Still, we observed increased reliance on forced choice card terms when presented a new odor and analyzed how test results were affected across trials by the effect of answer choice (free or forced). We tested for a learning bias using a cumulative-link mixed model learning (Agresti, 2002) with individuals as a random factor to account for.

3.6 Experiment Specific Methods

3.6.1 Market Smells 1 (independent samples, 2 difference open-air environments). We used direct solicitation for participants at two London food markets during October and November

2017. Borough Market is a semi-enclosed pedestrian zone with market stalls very close together and narrow pedestrian lanes located in Southwark, central London. St. Alban's market is a pedestrian street with stalls spaced widely apart in the St Peters Street retail area in St. Alban's city center, a north London commuter belt. Thirty-nine participants over the age of 18 were recruited, 19 at Borough Market and 20 at St. Albans Market, and asked to identify four odors (rose, cloves, eucalyptus, and menthol). The small sample size precluded successful model fitting to any distribution so we used the permutation test for resampling the data and hypothesis testing (Eudey et al., 2010).

3.6.2 Market Smells 2 (repeated measures, 3 different open-air environments). We used social media (e.g., Twitter, meetup.com), blogs (smellofevolution.com), word of mouth, and direct solicitation for participants in a repeated measures experiment. Testing was conducted on two separate days in 2018 (28 July, 4 August). Each test day, we had two groups (10am and 2pm). Nineteen participants over the age of 18 were recruited and subject to three trials of the five-odor identification test (Mueller et al., 2006): peppermint, orange, rose, fish, and garlic (replaces leather due to a lower identification rate for leather in UK populations). Testing commenced for all groups at the entrance area to the Tate Turbine Hall, continued under Southwark Bridge pedestrian area, and finished at the Borough Market food stalls. The Tate Turbine Hall entrance is in a no traffic zone with no food vendors nearby. The Southwark Bridge pedestrian area is a heavily trafficked zone with restaurants, buskers, and normal city smells (e.g., urine, cigarettes, food). The Borough Market is a sensory rich environment with many vendors of raw and cooked foods. Time between trials was 20-25 minutes. Between-market differences were tested using the La Place approximation in a GLMM with repeated measures (random factor=participant ID) using lme4 (Bates et al., 2015).

3.6.3 Market Smells 3 (repeated measures, 2 different laboratory environments). We recruited University of Roehampton students and staff to participate in a lab-based experiment. Testing was conducted in two labs at the same time of the day over three days (1-3 pm, 13-15 February 2019). Thirty participants over the age of 18 were recruited and subjected to two trials of the five-odor identification test. The first trial was conducted in a 'clean', well-ventilated a low-odor space. The second trial was conducted in the 'smelly' lab, a simulated market environment with the same experimental odors diffused one hour prior to testing. Smelly lab odors were garlic, coffee, madras curry paste, and caramel furanone (3% concentration). Time between trials was 15-20 minutes. Between-market differences were tested using the La Place approximation in a GLMM with repeated measures (random factor=participant ID) using lme4 (Bates et al., 2015).

3.6.4 Lab versus Field. We compared olfactory ability in the clean lab to those from MS1 and the first trial of MS2 to see if we find the same thing as the OFFE study—that the field environment is not significantly different from the lab environment. As mentioned above, we suspected this would not be the case due to participants familiarity of their own homes due to olfactory adaptation. Differences between the lab and the field were tested using the La Place approximation in a GLMM with repeated measures (random factor=participant ID) using lme4 (Bates et al., 2015).

4 ETHICAL CONSIDERATIONS

Field research for this project was approved by the University of Roehampton Ethics Committee, approval number LSC 17/ 213 (JCB, KCH). Written informed consent included asked volunteers to provide no further information beyond a name (signed and printed). Data collection sheets were labelled with a unique numeric ID. The unique numeric ID was not noted on the informed consent which means no personally identifying information was linked to test data. The data collection sheet included basic demographic information (sex, age, ethnicity, postcode []MS1 only), and olfactory ability scores.

5 RESULTS

5.1 Data Coding. All descriptive answers (whether free or forced choice) were coded as correct, near miss, far miss, and incorrect (Cain, 1979) by two observers (JCB, KCH). Inter-observer (JCB, KCH) code agreement was analyzed by Cohen's kappa (κ) using irr (Gamer et al., 2012) in the lpsolve package (Berkelaar, 2015). For MS1, the coding of descriptive data (n=153) did not differ significantly between two observers for free choice (κ= 0.556, p= 0.000); there were no forced choice data for MS1. For MS2, the coding of descriptive data (n=435) did not differ significantly between two observers for free choice or (κ= 0.537, p= 0.000) or forced choice (κ= 0.500, p= 0.000). For MS3, the coding of descriptive data (n=300) did not differ significantly between two observers for free choice (κ= 0.418, p=0.00) or forced choice (κ= 0.676, p=0.00). For all subsequent analysis we use the codes from KCH.

5.2 Data Exploration. Sample demographics are presented in Table 1. Self-chosen gender, in our samples, mapped to biological sex. We have almost double the number of females (n=61, 62%) than males (n=37, 38%) and a range of ages across experiments.

Table 1: Sample Demography

		Sample Size			Age				
		n	*Female*	*Male*	*18-24*	*25-34*	*35-44*	*45-54*	*55+*
Market Smells 1	St. Alban's	19	12	7	7	3	2	3	4
	Borough	20	11	9	7	5	4	3	1
Market Smells 2		29	17	12	7	9	5	4	4
Market Smells 3		30	21	9	18	0	7	3	2

The results of a correspondence analysis (Table 2) from FactoMineR (Le et al., 2008) using only free choice data for all experiments demonstrate an association between two variables, a combined age-sex variable and raw scores per odor (chisq= 85.35, p-value= 0.000). As expected, and based on previous studies discussed above, olfactory ability is better in females but, looking at the plot of associations from Factoshiny (Vaissie et al., 2018), no clear age-related pattern is present (Figure 1). The contribution to variance is driven large by young females, followed by males aged 25-34 (22%) and females aged 34-44—all other contributions are <10%. Subsequent analysis considered sex as a factor but not age.

Table 2: Correspondence Analysis Results (AgeSex * Raw Scores)

Eigenvalues	**Dim.1**	**Dim.2**	**Dim.3**
Variance	0.076	0.013	0.007
% of var.	79.182	13.829	6.988
Rows	**Dim.1**	**Contribution**	

1-Female	0.280	35.64
1-Male	-0.120	1.68
2-Female	0.202	2.97
2-Male	-0.447	21.61
3-Female	-0.305	11.80
3-Male	-0.249	6.71
4-Female	0.267	5.49
4-Male	0.048	0.30
5-Female	-0.251	4.01
5-Male	-0.397	9.78
Columns	**Dim.1**	**Contribution**
correct	0.225	29.90
far miss	0.088	0.91
incorrect	-0.366	63.10
near miss	0.208	6.09

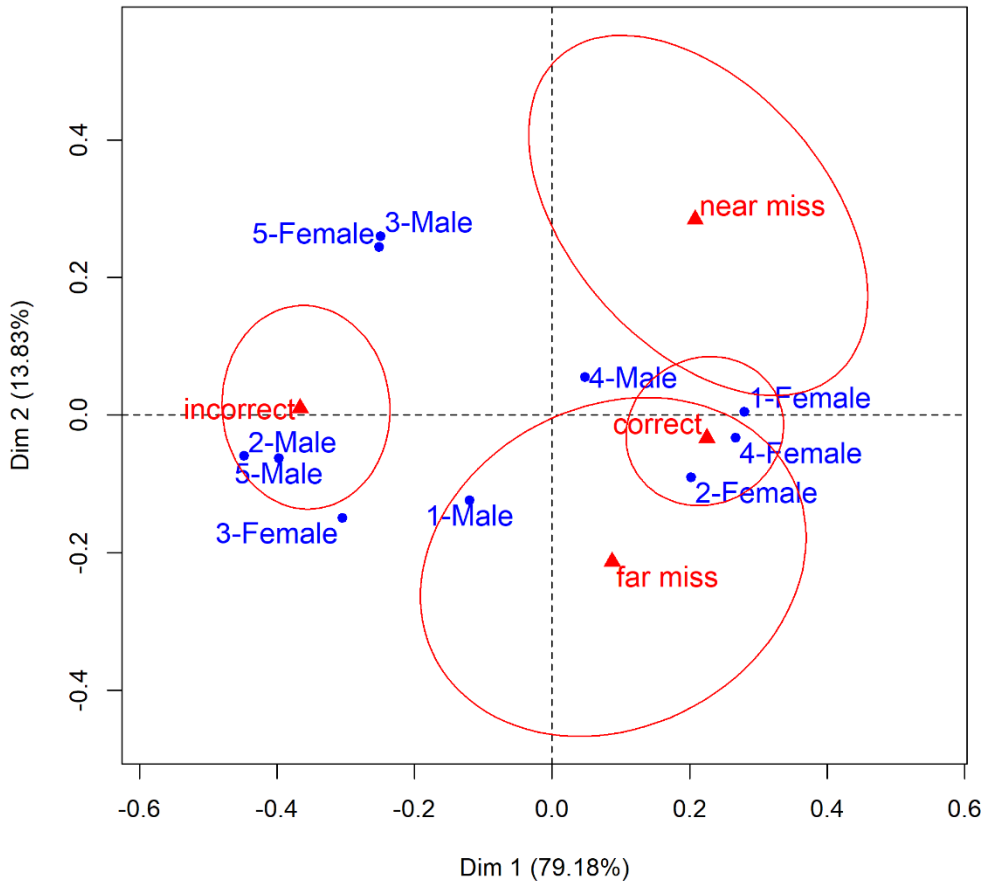

Figure 1: Correspondence analysis plot of olfactory ability score and age/sex. Age groups: 1 [18-24], 2 [25-34], 3 [35-44], 4 [45-54], 5 [55+].

5.3 Descriptive Terms. The distribution of abstract terms for free choice varied across samples (MS1: 2%, MS2: 4%, MS3: 47%) as did the use of products to describe odors (MS1: 19%, MS2: 5%, MS3: 27%). Most terms cluster around source or nonproduct but a correspondence analysis conducted in FactoMineR (Le et al., 2008) found significant associations between the age-sex variable and both abstract (chisq= 47.39; p-value=0.000) and product (chisq= 54.1, p-value= 0.000) terms. Plots of the analysis (Figure 11) were made in Factoshiny (Vaissie et al., 2018); the category *none* represents individuals who did not smell or were not able to identify the odor and the age groups are 1 [18-24], 2 [25-34], 3 [35-44], 4 [45-54], 5 [55+]). Generally, younger participants used source terms more consistently than abstract terms (Figure 11, left) or product names (Figure 11) while middle-aged participants (mostly male) uses abstract terms and product names some of times. For abstract words, the strongest trend is with the youngest females consistently using source names and the youngest two groups of males not able to provide a free choice response. Specifically, the youngest females have the strongest tendency toward nonproduct names and the youngest two groups of males are most commonly not able to provide a free choice response. The contribution to variance is driven large by young females, followed by males aged 25-34 and youngest males—all other contributions are <10%.

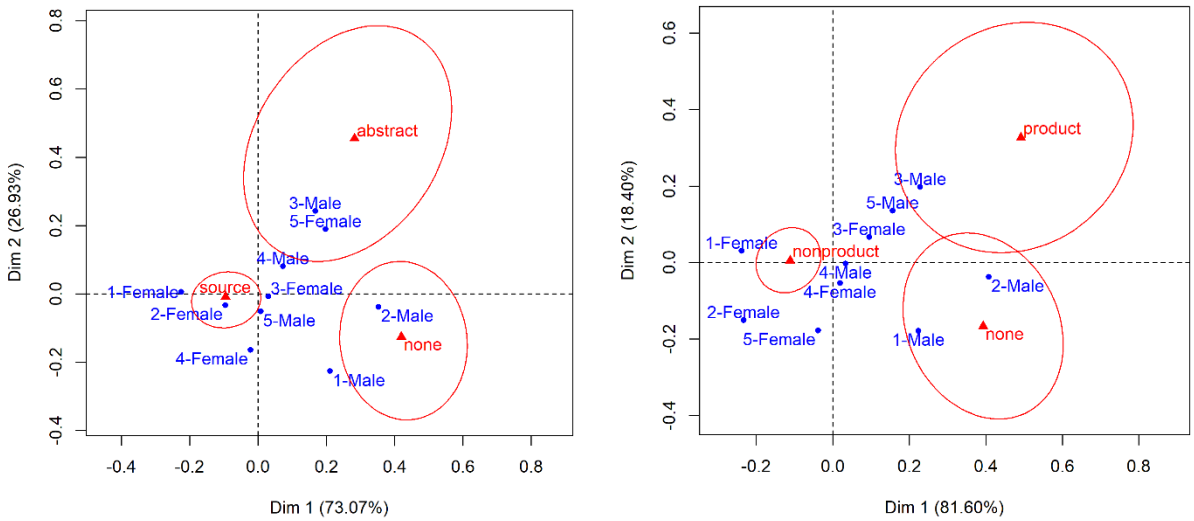

Figure 2: Correspondence plots for age and abstract terms (left) and age and product terms (right). Age groups: 1 [18-24], 2 [25-34], 3 [35-44], 4 [45-54], 5 [55+].

Table 3: Correspondence Analysis Results (AgeSex * Terms)

Abstract				**Product**	
Eigenvalues	**Dim.1**	**Dim.2**		**Dim.1**	**Dim.2**
Variance	0.037	0.014		0.047	0.011
% of var.	73.070	26.930		81.602	18.398
Rows	**Dim.1**	**Contribution**	**Rows**	**Dim.1**	**Contribution**
1-Female	-0.225	46.22	1-Female	-0.238	40.45
1-Male	0.211	10.90	1-Male	0.224	9.62
2-Female	-0.096	1.34	2-Female	-0.233	6.17
2-Male	0.353	28.75	2-Male	0.408	30.15

3-Female	0.029	0.22	3-Female	0.095	1.84
3-Male	0.167	6.06	3-Male	0.228	8.86
4-Female	-0.022	0.08	4-Female	0.019	0.04
4-Male	0.073	1.37	4-Male	0.033	0.23
5-Female	0.197	5.06	5-Female	-0.038	0.15
5-Male	0.007	0.01	5-Male	0.156	2.50
Columns	**Dim.1**	**Contribution**	**Columns**	**Dim.1**	**Contribution**
abstract	0.282	11.75	product	0.492	31.77
none	0.420	68.66	none	0.393	47.56
source	-0.096	19.60	nonproduct	-0.111	20.67

5.4 Free Description versus Forced choice. We used car (Fox et al., 2011) and MASS (Venables et al., 2002) to compare our data distribution to normal, lognormal, and gamma distributions (Figure 3). None is a perfect fit but most of our data points lie in the confidence intervals for gamma, which was then used for model fitting.

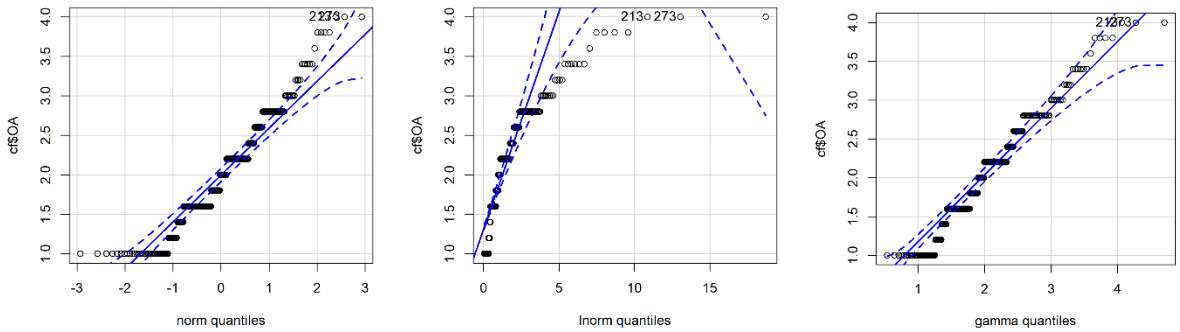

Figure 3: Distribution fitting (the solid line is the ideal fit and the dotted lines are the confidence intervals for the ideal fit).

We compared olfactory ability scores from free- and forced-choice data using the generalized linear mixed model in the lme4 package (Bates et al., 2015) with the La Place approximation (due to olfactory ability mean <5). The combined residuals of the model were not greater than the residual degrees of freedom (chisq= 13.479, ratio= 0.046, p-value=1) and the AIC was 408.7, both of which suggest high model accuracy. The inference from data visualization (Figure 4) that forced choice responses are higher than free was upheld by the GLM (Est= 0.085, Std. Err.= 0.013, t-value= 6.72, p-value=0.000). There was no significant effect from sex (Est= 0.-0.078, Std. Err.= 0.0521, t-value= -1.50, p-value=0.130). For the markets, the very last market in the trials has the best possible score and for the labs, there is marked difference between the first trial (clean) and the second (smelly).

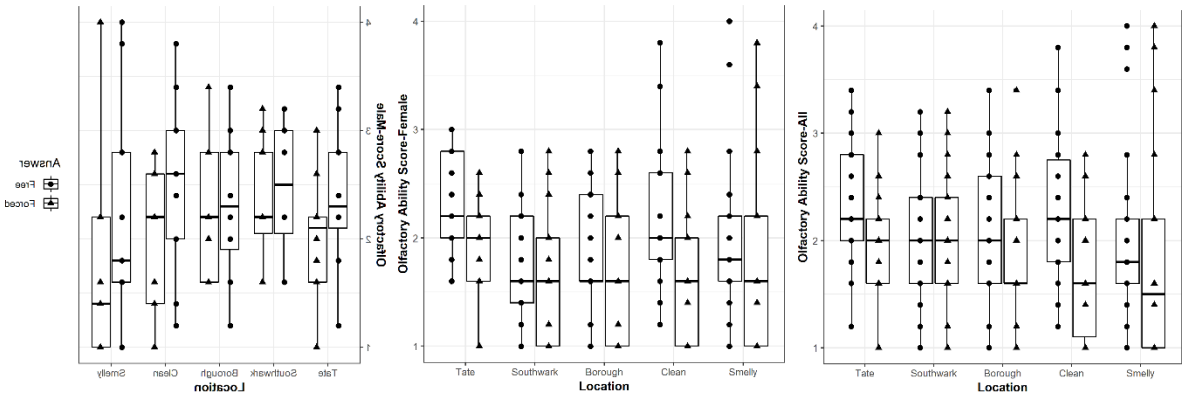

Figure 4: Boxplots of free versus forced data for olfactory ability by location: 1) all data, 2) female data, 3) male data

5.5 Odor learning. Data for this analysis were the ordinal ranked scores for each odor: 1-correct, 2-near miss, 3-far miss, 4-incorrect). The trellised boxplots were made with lattice (Sarkar, 2008) and indicate that there may be a learning bias. The work flow from left to right demonstrates an increasing bimodality where correct or incorrect forced choices from the card are consistent in repeat trials even if wrong (e.g., raspberry from forced choice always chosen for orange in subsequent trials). And, there is an increase in correct responses after seeing the forced choice card (before versus after).

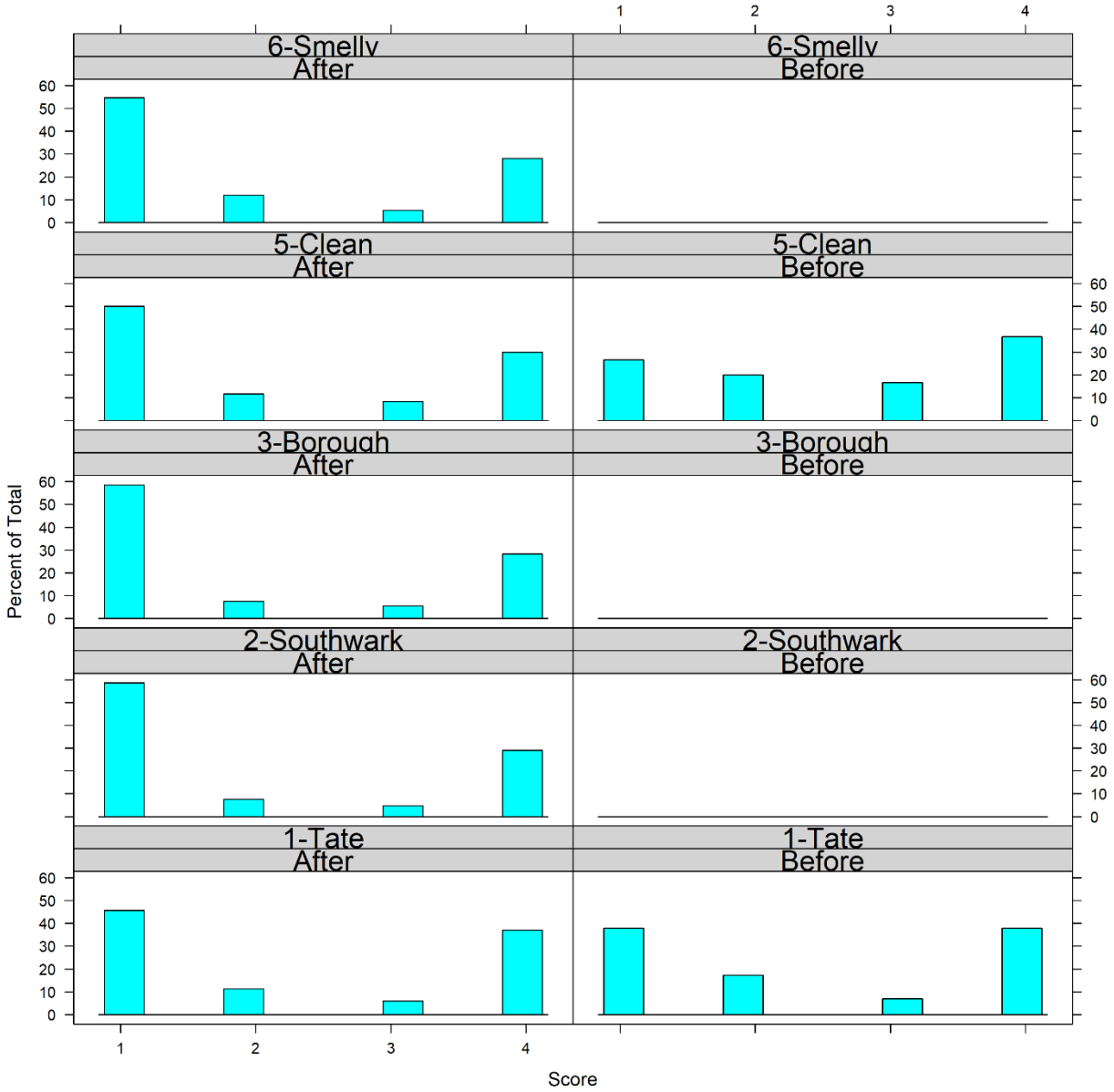

Figure 5: Boxplots of data by learning treatment, before seeing forced choice card and after. Only the first trial in MS2 (Tate) and MS3 (Clean) is included in before treatment. The bars represent the answers (correct, near miss, far miss, incorrect) partitioned according to learning treatment.

We considered the effect of learning by partitioning the data into control (no learning treatment, first free choice) experimental (learning treatment, forced choice) groups. Because we were interested in the effect of the forced choice card on learning, we limited our analysis to the first trial only (Tate for MS2 and Clean for MS3) and this avoided model noise from variation in location for the post-learning treatment data. We fitted six models using for two-way repeated ordinal regression (individual odor scores are ranked from 1-correct to 4-incorrect) using the Cumulative Link Mixed Model (clmm) in ordinal (Agresti, 2002). We used car (Fox et al., 2011)

and RVAdideMemoire (Maxime, 2019) ANOVA to compare fitted models to nulls (fixed, random) and rcompanion (Mangiafico, 2019) for pseudo r-squared values for model fit (Table 4).

When comparing the fitted model to the null with only a random effect, the fitted model was significantly better, as seen by the higher Nagelkerke pseudo r-squared values. When comparing the fitted model to the null with fixed effects only, there were no significant differences (note the extremely low Negelkerke values), which suggests little variation due to individual differences. There were no significant interactions or main effects in any of the models other than for learning treatment which confirms that learning from the forced choice card (whether correctly choosing or not) was taking place.

Table 4: CLMM results for learning (*significant values)

		Deviance			**Model*Null(random)**				**Model*Null(fixed)**			
		LRChisq	**df**	**p-value**	**LR**	**df**	**p-value**	**R^2***	**LR**	**df**	**p-value**	**R^2***
Model 1	Treatment	132.8	2	**0.00**	136	9	0.00	0.41	3.93	8	0.86	0.02
	Location	2.6	1	0.11								
	Sex	0.2	1	0.64								
	T:L	0.8	2	0.67								
	T:S	0.2	2	0.89								
	L:S	0.2	1	0.65								
Model 2	Treatment	134.1	2	**0.00**	135	5	0.00	0.40	3.32	4	0.51	0.01
	Location	2.5	1	0.11								
	T:L	0.8	2	0.66								
Model 3	Treatment	134.1	2	**0.00**	134	3	0.00	0.40	2.50	2	0.29	0.01
	Location	2.5	1	0.11								
Model 4	Treatment	130.8	2	**0.00**	132	5	0.00		0.33	4	0.99	0.00
	Sex	0.1	1	0.72				0.40				
	T:S	0.2	2	0.90								
Model 5	Treatment	130.8	2	**0.00**	132	3	0.00	0.40	0.13	2	0.94	0.00
	Sex	0.1	1	0.72								
Model 6	Treatment	132.0	2	**0.00**	132	2	0.00	0.40	0.00	1	1.00	0.00

*Nagelkerke estimate of pseudo R-squared

5.6 MS1 (independent samples, 2 difference open-air environments. The mean olfactory ability scores for Borough and St. Alban's were both 3.30 so we can conclude that there is no difference between markets. The mean olfactory ability for females was higher (3.17) than males (3.42)—the highest score is 1 and the lowest 4—and the median separation is even wider (Figure 1). The small sample size precluded successful model fitting to any distribution so we used the permutation test for resampling the data and hypothesis testing (Eudey et al., 2010). An approximate p-value was generated from simulated models (n-iterations=10^5) comprised of large random subsets of all possible data permutations (Eudey et al., 2010). There are no statistically significant differences in the sexes (p=0.116) but there is clearly a pattern that reflects previously documented superior female olfactory ability. One interesting qualitative observation in free choice data from Borough Market was references to frying smells, which suggests food-related odors were pulling focus. The experiment was underpowered in terms of sample size so the

question remains open whether background odors might influence differences in olfactory ability as measured by identification.

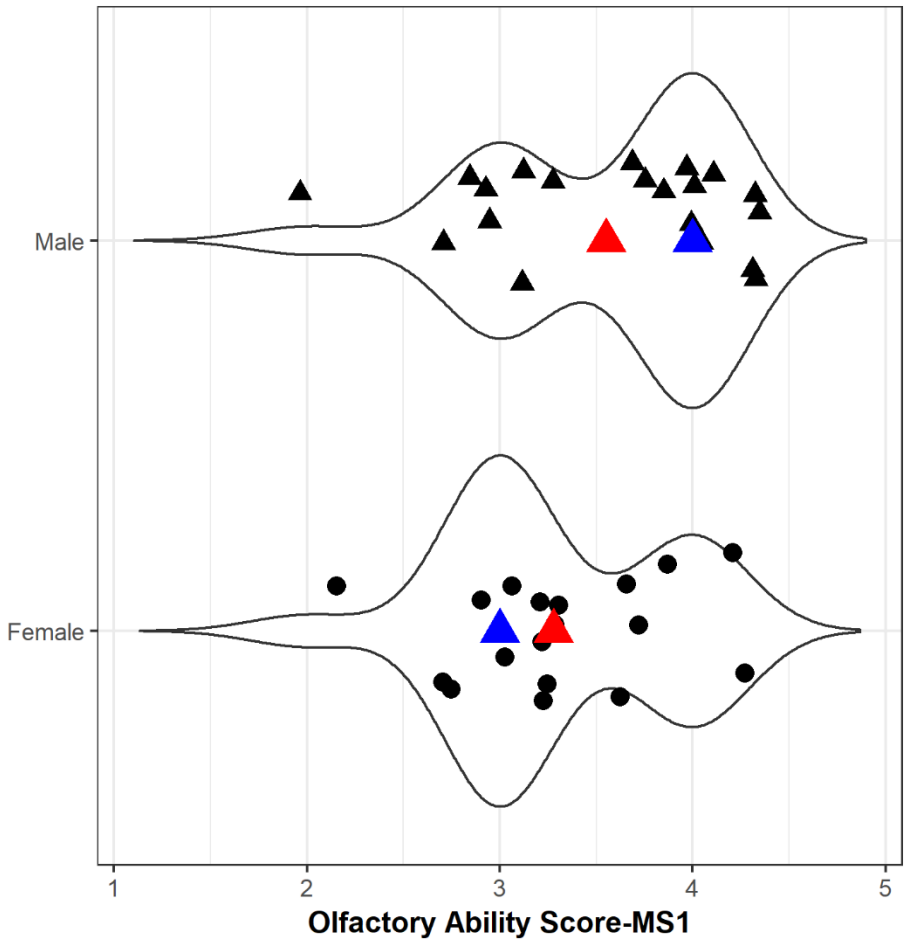

Figure 6: Violin plots of olfactory ability data distribution by sex for MS1. Red triangles are means, blue triangles are medians. The scale is from 1 (correct answer) to 4 (incorrect answer which includes those who cannot smell or identify the odor) with 2 (near miss) and 3(far miss).

5.7 MS2 (repeated measures, 3 different open-air environments). We used forced choice data for analysis because we know there is a learning effect. To use free choice data means that one of the five data points (free description) was solicited under a different condition than the other four. Violin plots of olfactory ability by market and sex (Figure 7) suggest that performance improves for females. A few points are worth noting. First, the female mean and the median grow closer together across trials and are the same at the last trial; the male mean and median exhibit the opposite trend, growing further apart across trials. Second, female olfactory ability scores are narrowly distributed compared to males, showing greater consistency. Third, contrary to the expectation that scores would decrease from Tate to Borough as the olfactory stimulation from the environment increased, females exhibit the opposite trend.

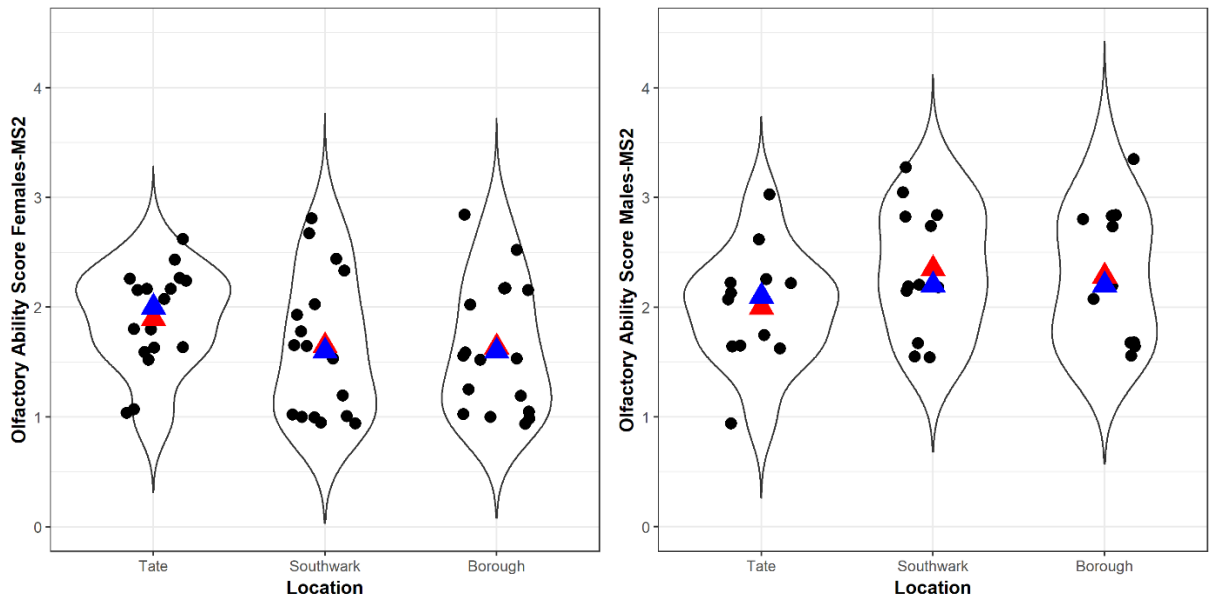

Figure 7: Violin plots of olfactory ability data distribution by market (females left, males right) for MS2. Female data are forced to y-axis scale of male data (which has a wider distribution of olfactory ability scores). Red triangles are means, blue triangles are medians. The scale is from 1 (correct answer) to 4 (incorrect answer which includes those who cannot smell or identify the odor) with 2 (near miss) and 3(far miss).

We used car (Fox et al., 2011) and MASS (Venables et al., 2002) to compare our data distribution to normal, lognormal, and gamma distributions (Figure 8). None is a perfect fit but most of our data points lie in the confidence intervals for the log normal distribution, which was then used for model fitting.

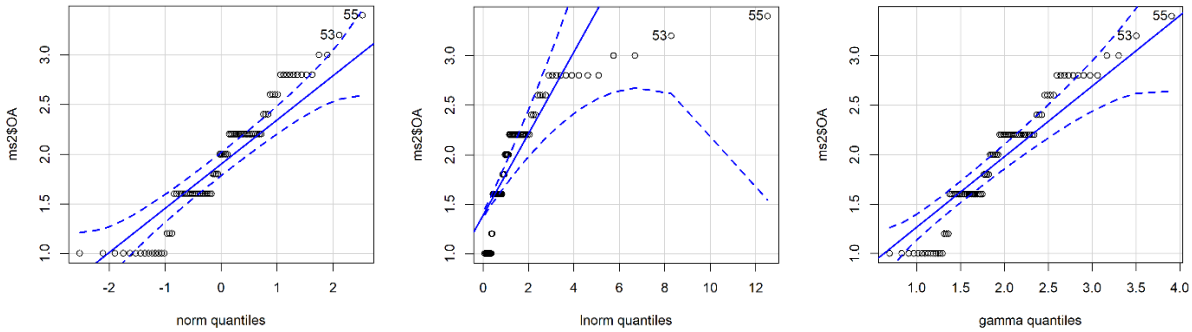

Figure 8: Distribution fitting (the solid line is the ideal fit and the dotted lines are the confidence intervals for the ideal fit).

We compared olfactory ability scores for between-market differences using the generalized linear mixed model in the lme4 package (Bates et al., 2015) with the La Place approximation (due to olfactory ability mean <5). The combined residuals of the model were not greater than the residual degrees of freedom (chisq=13.268, ratio= 0.162, p-value=1) which suggest high model accuracy but the AIC was low (132). The inference from data visualization (Figure 7) that

olfactory ability scores improve for females but not for males is slightly supported by the GLM results, which found significant sex differences but with small effect (Est= -0.129, Std. Err.= 0.057, t-value= -2.24, p-value=0.025). There was no significant effect from market.

5.8 MS3 (repeated measures, 2 different laboratory environments). As with MS2, we used forced choice data for analysis because we know there is a learning effect. Violin plots of olfactory ability by lab and sex suggest some sex-based differences. Female performance does not change much but the mean and median separate slightly (Figure 9, left). A different trend is noted for male performance which improves in the smelly lab, with the mean increasing slightly and the median increasing at a greater rate (Figure 9, right).

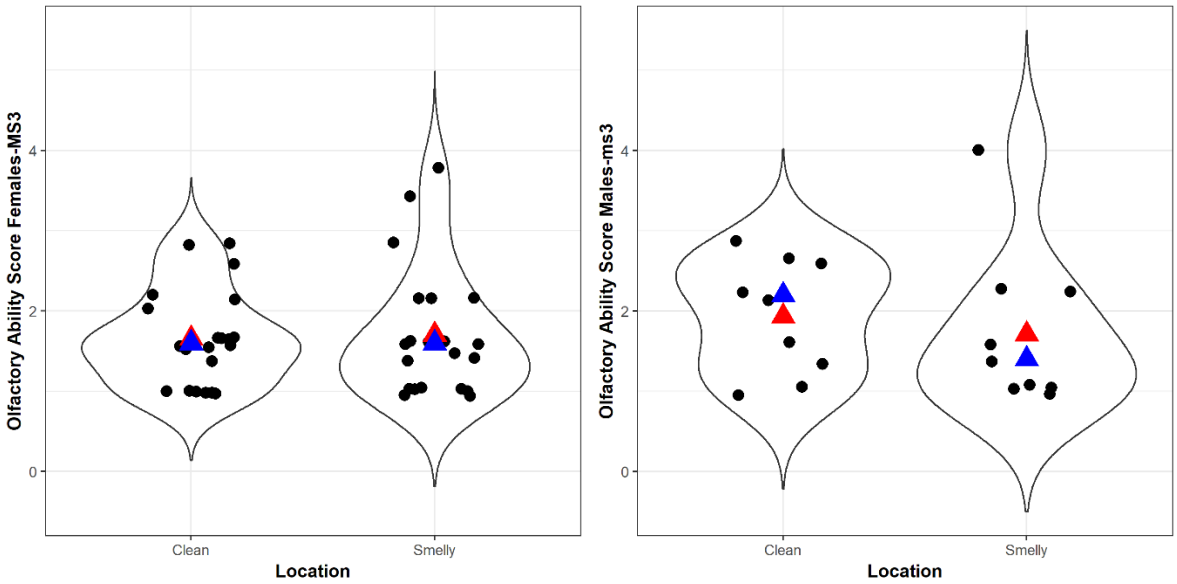

Figure 9: Violin plots of olfactory ability data distribution by market (females left, males right) for MS2. Female data are forced to y-axis scale of male data (which has a wider distribution of olfactory ability scores). Red triangles are means, blue triangles are medians. The scale is from 1 (correct answer) to 4 (incorrect answer which includes those who cannot smell or identify the odor) with 2 (near miss) and 3(far miss).

We used car (Fox et al., 2011) and MASS (Venables et al., 2002) to compare our data distribution to normal, lognormal, and gamma distributions (Figure 10). Each is a decent fit but most of our data points lie in the confidence intervals for the gamma distribution, which was used for model fitting.

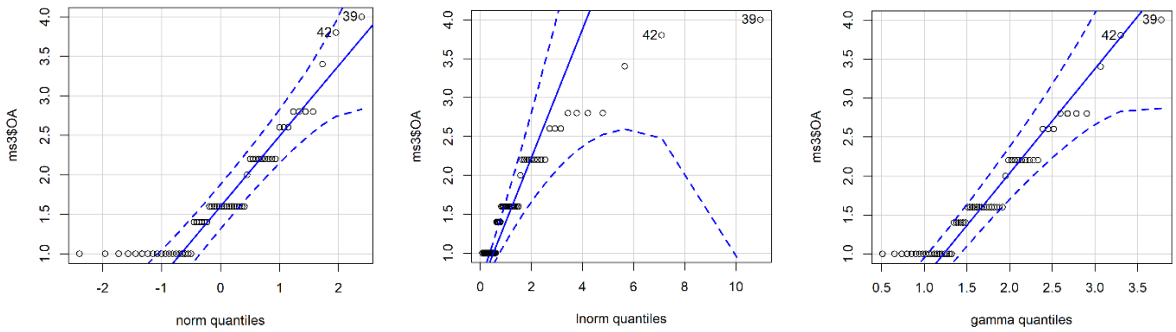

Figure 10: Distribution fitting (the solid line is the ideal fit and the dotted lines are the confidence intervals for the ideal fit).

We compared olfactory ability scores for between-market differences using the generalized linear mixed model in the lme4 package (Bates et al., 2015) with the La Place approximation (due to olfactory ability mean <5). The combined residuals of the model were not greater than the residual degrees of freedom (chisq=2.267, ratio= 0.041, p-value=1) which suggest high model accuracy but the AIC was low (82.9). The inference from data visualization (Figure 7) that olfactory ability scores improve for males but not females is not supported by the GLM which found no significant sex differences. There was also no significant effect from market.

5.9 Lab versus Field. We used free choice data for the lab to field comparison, which allowed us to include data from Market Smells 1. But, to minimize the learning bias effect, we tested the first trials of free choice data. The box plot (Figure 9) suggests that olfactory ability is better in the lab (lower scores) than the field.

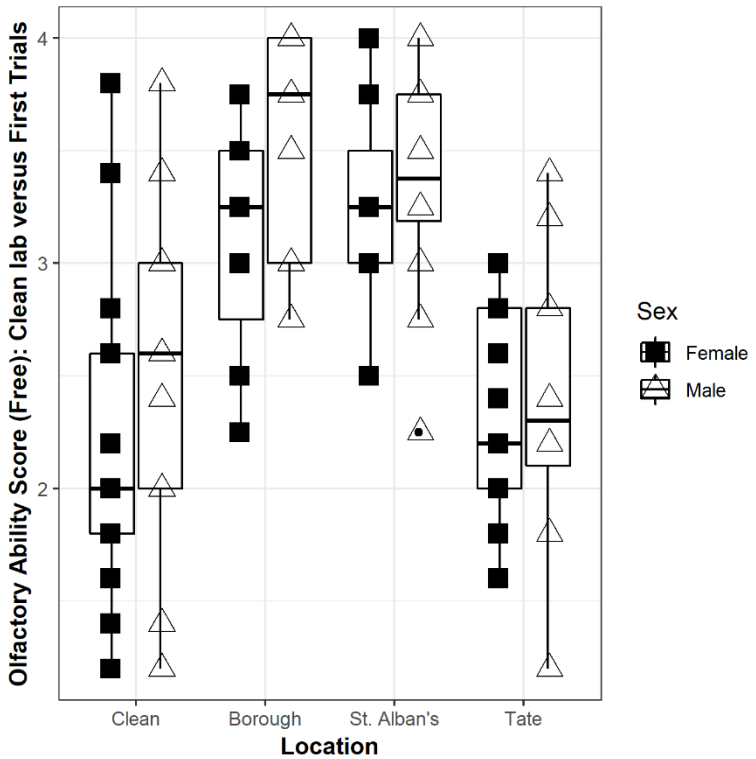

Figure 11: Box plots of olfactory ability data for first trials by market (forced choice on left, free choice on right) for MS2.

Data fit within the normal distribution (Fig. 10) so we used lme4 (Bates et al., 2015) for model fitting and car (Fox et al., 2011) for model assessment. The model AIC score was decent (215.8) with significant differences in both sexes (Est.= -0.584, Std. Err.= 0.188, t-value= -3.107, chi-sq= 14.605, df= 1, p-value= 0.000) and location (Est.= 0.285, Std. Err.= 0.166, t-value= 1.724, chi-sq= 4.245, df=1, p-value= 0.039), as predicted by the data visualization. There are no significant interactions between sex and location (Est.= 0.021, Std. Err.= 0.320, t-value= 0.065, chi-sq=0.004, df=1, p-value= 0.948) which means that the sex-based differences are likely attributable to superior female olfactory ability and the location-based differences are likely attributable to superior lab-based scores (except for males at Tate). Thus, we can conclude that smelling outside the lab diminishes olfactory ability.

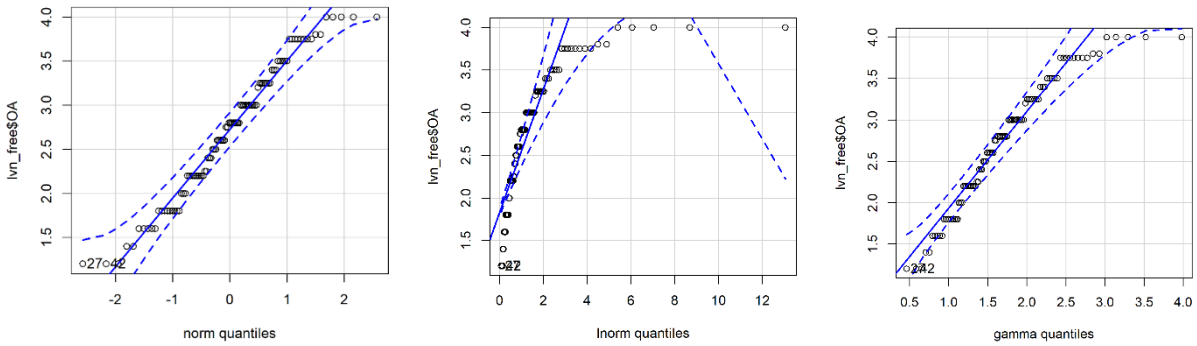

Figure 12: Distribution fitting (the solid line is the ideal fit and the dotted lines are the confidence intervals for the ideal fit). Forced choice, left. Free choice, right.

DISCUSSION AND CONCLUSION

We were interested in evaluating the portability of the odor identification tests to the field. We used the lab-validated short odor identification test (Mueller et al., 2006) and odor familiarity had been validated in our UK-based population (Neumann et al., 2012). Thus, we were testing the utility of the assay in the field, which had not yet been done.

We had two primary issues surrounding the field use of the odor identification test. First, odor identification is a complex process involving both prior experience with the odor and memory of that odor. Indeed, consistent labelling of an odor has been shown to enhance odor recognition (Rabin et al., 1984). On the one hand, odor identification is challenging for most subjects and the forced choice method was developed to overcome individual variation in odor experience and increase performance accuracy (Hummel et al., 2007; Negoias et al., 2010). On the other hand, forced-choice methods pull focus from the odor to a process of elimination and guesswork, which may mask true olfactory ability (Kern et al., 2014).Thus, we were concerned that the forced choice method for odor identification would impact our results. We compared olfactory scores for free and forced choice response and found that forced choice methods increased accuracy in odor identification. Second, the forced-choice test exposes the participant to the correct answer for the task. Exposure to correct answers appear not to have affected validation of the five-odor test in labs (Mueller et al., 2006) but labs have the luxury of longer between-test gaps. Field methods cannot rely on retention of participants over long periods for repeat testing and we were concerned that participants would learn from the card rather than evaluating each odor anew. We found a significant effect from the use of forced choice methods on olfactory ability scores. Participants relied increasingly on terms from the card, even if they were not correct. For example, describing orange as fruity and sweet at first smell was replaced by the correct answer of orange or, quite often, the incorrect answer of raspberry in each subsequent trial. Further, participants increasingly ignored the card when it was presented to them because they held in mind the answer from the last trial. The masking of true olfactory ability by learning is a confounding factor in a repeated measures design. Thus, odor identification is not ideal for the field due to score inflation from forced choice and learning bias from forced choice. Collecting free choice data has value if interested in term choice. We feel that free choice better reflects a genuine olfactory ability compared to the forced-choice method which has been shown to increase accuracy in identification performance (Hummel et al., 2007; Negoias et al., 2010).

In addition to field-testing methods, we were interested in broader questions about the human ecology of olfaction. Specifically, we were interested in whether environment significantly altered olfactory ability. There were no differences between markets, one in a polluted are and one in a less polluted area. There were no differences in repeated measures across three locations, one low odor, one polluted, and one awash with food smells. Finally, there were no differences between lab settings, one a low-odor control and one an experimental set-up to mimic food market smells. We are not sure if the learning bias in our repeated measures tests reduced power to find a significant difference that might otherwise have been found. In comparing our lab results to those in the field, we found significant differences. We did find some age-based patterns in free choice wherein younger participants tended strongly to use

source terms and middle-aged participants tended to use additional descriptors including abstract terms and product names. This reflects a noted tendency for odor learning and labelling competency to increase with age (Doty et al., 1984a; Larsson, 1997; Larsson et al., 2003; Lehrner, 1993; Rabin et al., 1984).

Our data suggest that our sense of smell is heavily disrupted in the built environment compared to ideal conditions and that smelling in the wild may be disruptive to individual ability to smell what is literally right under the nose (Hoover, 2018a). While this result might be expected, it is important because current olfactory ability data rely on lab studies of WEIRD populations and are extremely non-representative. While it may seem intuitive to argue that lab results are better than results obtained from various public outdoor locations, we feel it is very important to state because data from indigenous and traditional or small-scale societies cannot be collected in a lab. Thus, we are not comparing data collecting under similar circumstances and cannot conclude that one population has superior olfactory ability or not. Even if the argument that high scores in the field compared to the lab indicate better ability under worse circumstances, we do not know this is true without testing it by collecting data in the field on subjects in WEIRD countries too. Ultimately, there are no data to suggest that individuals performing well in the lab, perform well in the field and likewise for those not performing well in the lab. Smelling odor mixtures with variable environmental conditions is very different from smelling single odors in a pure form delivered to the nose. Naturally, lab-based testing is a strong component of health screenings to diagnose clinically poor sense of smell. But, field-testing is necessary to understand the ecology of human olfaction.

An issue related to those raised by comparing WEIRD lab results to field-collected results is that of sex differences in performance. We found the same sex-based trends in olfactory ability (higher female scores) as reported in other studies (Dalton et al., 2002; Doty et al., 1985; Doty et al., 2009; Oliveira-Pinto et al., 2014). Females performed better with an average of 2.35 for free choice and 1.71 for forced choice compared to males with an average of 2.67 for free choice and 2.05 for forced choice. A score of 1-2 suggests normal healthy functioning while a score of >3 suggests hyposmia, or olfactory dysfunction. Males in our study fall into the latter group with females on the boarder (depending on which score is used). Superior female olfactory ability has been partly attributed to better learning (Doty et al., 1984a; Ferdenzi et al., 2013; Larsson, 1997; Larsson et al., 2003; Lehrner, 1993). Will this finding persist in field-based studies globally in diverse populations and natural settings? We think it will and suggest an evolutionary ecology argument for superior female olfactory ability—females are better foragers and produce most foraged food. We note that the participants who referred to a frying smell at Borough Market in Market Smells 1 were all female. Is this better ability a result of deeper interaction with nature to find food? Is better ability biological, cognitive (learning or remembering odors), or genetic?

We were interested in field-based methods testing and understanding the impact of the natural (in this base, built) environment on human olfactory ability. Our data align with previous findings for superior female olfactory ability and demonstrate that lab environments generate very different olfactory ability assessments than olfactory ability in daily life. Results raise interesting ecological questions about adaptation relative to odor identification and food foraging, an activity that makes a large contribution to survival and reproduction. What is the evolutionary and biological significance of better olfactory ability or better learning ability in females? We

also identified some methods challenges when translating lab methods to the field, mainly the issue of learning (particularly in repeated measures) and improved performance form forced choice methods. The odor identification test was quick and easy to deliver but not an ideal field method for assessing olfactory ability. The deeper implications of our findings are that we must expand data collection methods to generated field-based data in all societies so that we can test differences in olfactory ability using the same methods and we can evaluate the salience of lab findings in natural ones.

This paper is the first to apply anthropological principles to olfactory science in the sense that if we are to truly capture what human olfactory ability is, we will have to collected field-based data from globally distribution populations, including indigenous populations. As field-based anthropologists know, lab conditions cannot be recreated in the field not can indigenous populations be tested in a lab. Thus, we need field-based data for human olfactory ability in industrialized populations for more robust anthropologically-driven comparisons to field-based data in indigenous populations if we are to arrive at a true understanding of olfactory ecology setting. This study is a valuable first step in exploring the human ecology of olfaction.

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