

Article

Electronic Nose Profiling of Pet Foods for Brand and Flavor Discrimination with Preference Analysis

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Abstract

Electronic nose (EN) technology, based on electrochemical sensor arrays, has emerged as a rapid and objective tool for aroma characterization in food systems. This study investigated factors influencing cat food preference using physicochemical analysis, texture measurement, preference testing, and EN technology. Nine (9) commercial cat foods from three brands (A: premium; B and C: medium price) with different flavors were evaluated. Proximate analysis revealed no significant differences ($p > 0.05$) in most nutrients, except crude fiber (CF) ($p < 0.05$), which was higher in lower-priced cat foods. Shear force showed a positive correlation with consumption ($r = 0.72$), while CF was negatively correlated ($r = -0.52$). Preference tests indicated that Brand A was most preferred, followed by Brand C, while Brand B was least preferred. Principal component analysis (PCA) identified variability in individual cat preferences, and one outlier cat was excluded. Discriminant analysis of EN data showed clear separation by brand rather than flavor, suggesting brand-related aroma profiles can be monitored rapidly through the digital odor fingerprint. Cat food acceptance is mainly driven by texture, CF content, and aroma rather than macronutrient composition. The results of the EN evaluation of cat food samples revealed the same group similarities and differences as the 8-month preference test performed with cats. Similar to this study, EN classification models can be developed using food preference data and the digital aroma fingerprints of foods. After validations, the EN models can be used as an effective tool to monitor the quality and assess new diets according to the known preferred odor fingerprint.

Keywords: aroma; pet food; artificial sensing; machine olfaction; smell; odor; companion nutrition



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1. Introduction

The domestic cat (*Felis silvestris catus*) is an obligate carnivore that exhibits a feeding behavior closely linked to its strict carnivorous physiology and specific nutritional requirements [1]. Cats have a high dietary protein requirement due to their elevated nitrogen needs [2]. They can regulate the activity of enzymes involved in the first irreversible step

of essential amino acid degradation, which explains why their requirements for individual essential amino acids are not disproportionately high [3]. However, cats have a limited ability to downregulate aminotransferases and urea cycle enzymes. As a result, they continuously metabolize amino acids [4] and can readily use them for gluconeogenesis and energy production [5]. Because of the low activity of certain enzymes involved in nutrient synthesis, cats have obligatory dietary requirements for several nutrients that are not essential in many other species [6]. These include the amino acids arginine and taurine [6], as well as niacin, vitamin A, and vitamin D [7]. Among fatty acids, arachidonic acid is essential for cats because, unlike dogs, they cannot synthesize sufficient amounts from linoleic acid [8]. Their feeding pattern typically involves consuming small meals throughout the day, reflecting the behavior of their wild ancestors (*Felis silvestris lybica*) that preyed on small animals [9,10].

Diet selection in cats is influenced by sensory attributes such as aroma, taste, texture, and temperature [10–13]. Among these, aroma plays a critical role, with cats showing a strong preference for umami-rich foods associated with high amino acid content [14]. Cats can also regulate their nutrient intake by selecting foods that balance their dietary requirements [15].

The global pet food industry has grown significantly, driven by continuous product innovation aimed at meeting both nutritional and sensory expectations of pets and their owners [16,17]. Product development is guided by key performance criteria, including palatability [18], texture [19], and flavor [11], leading to innovations in pet food formulation. To evaluate these attributes, the pet food industry traditionally relies on animal-based testing models, notably the single-bowl acceptance test and the two-bowl (forced-choice) preference test [20]. The single-bowl test measures food intake over a defined period and provides an indication of acceptability, but does not assess preference or degree of liking, whereas the two-bowl test allows animals to choose between two food samples, making it useful for comparative evaluations [21]. The limitation of the latter technique includes reduced effectiveness when products are similar, the inability to identify specific drivers of preference, and dependence on reference samples [21].

Flavor evaluation in pet food is particularly challenging due to the complexity of interactions between aroma and taste [22]. Conventional analytical methods, such as gas chromatography–mass spectrometry (GC-MS), are widely used to identify volatile compounds in pet food; however, they are labor-intensive, costly, and may not directly correlate with sensory perception or animal preference [23]. Furthermore, animal preference tests are time-consuming, expensive, and require a trained animal behavioral expert, with outcomes often influenced by individual variability [24].

The electronic nose (EN) technologies using arrays of various sensors or separation techniques to detect volatile compounds and generate characteristic digital aroma fingerprints, simulating aspects of the olfactory system have emerged as rapid and more objective tools for aroma characterization [25,26]. The EN technology has received considerable attention in food research [27], which is evident in recent studies involving the discrimination of wine type [28], detection of adulteration in rice by aroma profiling [29] and the development of a transfer-learning scent former model for food characterization based on smell [30]. It is important to emphasize that EN and GC-MS systems complement each other in the sensory evaluation of pet food [31].

This current study was designed to assess whether electronic nose-derived aroma fingerprints can differentiate commercial cat food products and serve as an objective indicator of feline palatability in relation to physicochemical characteristics and preference test results. The novelty of this study is that it intends to integrate long-term feline preference testing,

physicochemical characterization, texture analysis, and EN technology to demonstrate that digital odor fingerprints correspond closely with actual cat food preferences.

2. Materials and Methods

The experimental design, including cat food samples, chemical analyses, texture measurements, animal preference testing procedure, and statistical evaluation, was reported previously by Éles et al. [32].

2.1. Cat Food Samples

Cat foods with three different flavors (chicken, lamb, and tuna) from three commercial brands (A, B, and C) were used in the experiment. The authors concealed the true brand identity to avoid brand-related controversy. Sample 1: brand A—chicken flavor; 2: A-lamb; 3: A-tuna; 4: B-chicken; 5: B-lamb; 6: B-tuna; 7: C-chicken; 8: C-lamb; 9: C-tuna. Price may reflect the quality of raw materials and the production process; therefore, brand A was rated as premium quality, brand B and C were rated as medium quality.

2.2. Chemical Analyses of Food Samples

The proximate composition of the foods was quantitatively determined using standard laboratory procedures, including analyses of moisture content, ether extract, crude protein, crude fiber, and ash [33]. All chemicals used were of analytical reagent grade, from Sigma-Aldrich (Schnelldorf, Germany). Nitrogen-free extract (NFE) was calculated from the proximate analytical composition according to the following equation:

$$\text{NFE (\%)} = 100 - (\text{crude protein} + \text{ether extract} + \text{crude fiber} + \text{ash} + \text{moisture}).$$

2.3. Texture of Food Samples

The mechanical properties of the dry cat food products were evaluated using a Zwick-Roell Z005 universal testing machine (Zwick GmbH, Ulm, Germany). For each determination, intact kibbles were transferred into a cylindrical sample holder (50 mm internal diameter) and compressed using a piston with a diameter of 44 mm. Compression was continued until the sample reached 80% of its initial filling height, after which the peak force generated during the test was recorded using testXpert v11.0 software. Shear force values were expressed as N/mm² and used as an indicator of kibble hardness. To minimize the influence of sample heterogeneity and improve measurement reliability, 15 independent replicates were performed for each cat food formulation, and the resulting values were used for subsequent statistical analyses [32].

2.4. Preference Tests

The preference test was performed at the University of Veterinary Medicine, Budapest, Hungary (legal predecessor: Szent István University, Faculty of Veterinary Medicine). The study was conducted in accordance with the Directive 2010/63/EU (European Parliament and Council of the European Union, 2010) for the care and housing of animals used for scientific purposes. The preference test used in the present study was reviewed by the Institutional Animal Care and Use Committee of Szent István University, and was conducted under the ethics approval of the code: No. 22.1/5/003/2010.

Seven castrated domestic shorthair cats (3.2 ± 0.3 years, 3.44 ± 0.38 kg) were included in the preference test. During the preference test, cats were temporarily housed individually in appropriately sized enclosures to prevent interference between conspecifics. The preference test period consisted of 12 subunits. Within the subunits of individual testing sessions (8 days), animals were continuously monitored, and cats were returned to the group housing immediately after completion of the preference assessment. The cats were

free to move within their enclosures, and food and water were provided ad libitum. The study consisted exclusively of feed choice observation (measurement of feed intake). No invasive procedures, biological sampling, restraint, food deprivation or procedures causing pain, suffering, distress or lasting harm were performed.

During each subunit, three out of nine different cat food samples were tested for each cat over eight days. The position of the bowls was changed each time to reduce laterality effects. The weight of the leftovers of each food was measured daily against the offered weight of the respective food, and the preference over the entire testing period was described by the consumed ratio of each food, in percentage [% = (consumed/offered) × 100]. A 10-day control (washout) period was maintained between subunits, during which the cats were placed in groups and fed a standard cat diet (beef).

2.5. Electronic Nose Measurements

The batches of the cat foods used for the preference test were sampled and the pooled samples were stored at 4 °C until the instrumental aroma measurement at the end period of the preference test. The volatile aroma profiles of the cat foods were characterized using an α Fox4000 electronic nose (Alpha M.O.S., Toulouse, France), equipped with an array of 18 metal oxide semiconductor (MOS) sensors. The applied commercial EN did not require any daily calibration protocol. Approximately 1 g of each sample was placed into a 20 mL hermetically sealed headspace vial and allowed to equilibrate before analysis to promote partitioning of volatile compounds between the sample matrix and the headspace.

Headspace sampling was carried out automatically using an Alpha M.O.S. HS100 autosampler, which injected 1000 μ L of headspace gas into the sensor chamber. Throughout the analysis, synthetic air served as the carrier gas at a constant flow rate of 150 mL min^{−1}. Samples were incubated at 40 °C for 120 s before injection to standardize volatile release. Each analytical cycle consisted of a 120 s sensor acquisition period, followed by a 1200 s recovery interval to allow complete regeneration of the sensor array before the next measurement.

To account for instrumental variability and day-to-day drift, measurements were distributed over 10 consecutive experimental days. Every cat food sample was analyzed three times per day in a randomized sequence, yielding 30 electronic aroma fingerprints per product and a total of 270 measurements across the nine commercial cat food [34].

2.6. Data Analysis

2.6.1. E-Nose Data

An interfaced PC running AlphaSoft v10 (Alpha M.O.S, Toulouse, France) operated the EN and saved raw EN sensor values in the form of relative resistance changes ($\Delta R/R_0$). The minimum or maximum extreme value of the relative resistance change was saved for each sensor as the sensor's intensity, resulting in an aroma fingerprint described by 18 variables. The classification of cat food samples was performed based on this multivariate dataset using canonical discriminant analysis (DA) in IBM SPSS 20.0. DA was verified by hit rate (i.e., ratio of correctly classified records) in cross-validation. The cross-validation of the classification models was performed with leave-one-day-out cross-validation, when one day of measured data was left out of the modelling and was used for testing, in an iterative approach. The distances of the group centroids were calculated based on the weighted distances along the first two axes of the DA models—weighing was based on the percentage of the explained variance of the relevant axis [34].

2.6.2. Statistical Evaluation of the Data from the Proximate Analysis of Food Brands

One-way analysis of variance (ANOVA) was conducted in IBM SPSS 20.0 software to evaluate differences in the nutrient compounds of the cat food brands (A, B, and C).

Statistical significance was determined at 5% significance level ($p < 0.05$). A correlation analysis was subsequently performed to assess the relationship between significantly different food components and consumption.

2.6.3. Statistical Evaluation of the Food Consumption Data

The treatments (i.e., feeding the different diets) are not independent of each other, as stimuli placed in the same space influence each other's effects, and these effects are mixed with each other [35]. Since the data did not show a normal distribution, and this could not be achieved with the arcsine transformation, Kruskal–Wallis and Mann–Whitney non-parametric statistical tests were used to detect significant differences between the median values, using IBM SPSS 20.0 software. During the analysis of outliers, data outside the two standard deviations were excluded.

The database was analyzed using principal component analysis (PCA) in R Project with the FactoMineR package (<https://doi.org/10.32614/CRAN.package.FactoMineR>) to confirm data homogeneity and identify possible outlier consumption patterns among individuals. Cats have distinct personalities due to a complex mix of genetics, early life experiences, and environmental factors, leading to a broad spectrum of unique behavioral differences [36]. Therefore, it is important to identify the strong behavioral variations and exclude individuals that can negatively influence the evaluations of general feline behavioral patterns. Based on the data evaluation method of [37], a database was created in which the arcsine-transformed percentages of the daily food intake of the cats were arranged in adjacent columns for each cat per sub-experiment. Given that in each subunit of the experiment the cats chose from three foods at a time, knowing the consumption rates of two foods, the third data point is derived from these. According to the methodology followed [37], three PCAs were run with the double combinations of the three different cat foods fed in the single subunits of the experiment: each PCA included consumption data of two bowls out of the three bowls provided in the subunits of the experiment, i.e., PCAs were run with data of bowl 1 & 2, 2 & 3, and 1 & 3. The PCA results were evaluated visually using the 2-dimensional score plots of the 1st and 2nd principal component (PC), and by evaluating the centroid distances of the cats. Pairwise distances were calculated using the squared Euclidean distance of the first eight, orthogonal, variance-normalized principal component scores (covering cca. 80% of the variance of the original variables), resulting measures mathematically identical to the classic Mahalanobis distance in the original variable space [38] (see Figures S1–S3 in Supplementary Material).

3. Results and Discussion

3.1. Evaluation Based on Laboratory Measurements

Table 1 summarizes the results of proximate analysis and sheer force of three (3) cat food brands classified as premium (Brand A) and medium quality (Brands B and C) across chicken, lamb, and tuna variants [32]. Ash content was lower in Brand A compared to Brands B and C. Crude protein varied across treatments, with the highest value observed in Brand B chicken. Ether extract (fat) was generally higher in Brand A, while crude fiber was markedly lower in Brand A compared to the other brands, presumably due to the addition of non-animal proteins to obtain cheaper products. Nitrogen-free extract values were slightly higher in Brand A, indicating relatively greater soluble carbohydrate content [39]. Shear force values ranged from 0.90 to 1.38 N/mm², reflecting tendencies of differences ($p > 0.05$) in texture among samples, as the chicken flavor of brand A (sample 1) was the hardest among all samples. Statistical analysis showed that amongst the proximate components, only crude fiber differed significantly among brands ($p < 0.05$), while all other parameters showed no significant differences ($p > 0.05$).

Table 1. The nutrient content (%) and texture of the examined cat foods (from Éles et al., 2015 [32]).

	DM	Ash	CP	EE	CF	NFE	Sheer Force (N/mm ²)
Brand A							
chicken	95.26	5.14	31.62	16.66	0.2 ^a	41.64	1.38
lamb	95.05	5.21	31.89	15.23	0.2 ^a	42.52	0.93
tuna	94.4	4.86	30.64	15.05	0.34 ^a	43.51	0.98
Brand B							
chicken	92.91	8.15	34.88	14.55	2.7 ^c	39.63	1.12
lamb	92.28	7.55	29.63	13.69	2.3 ^c	39.11	1.09
tuna	92.75	7.44	30.5	15.71	2.3 ^c	36.8	1.06
Brand C							
chicken	92.67	7.65	30.39	11.89	1.4 ^b	41.34	1.11
lamb	93.32	7.58	33.45	12	1.4 ^b	38.89	0.9
tuna	93.56	7.91	32.36	11.54	1.4 ^b	40.35	1.15
p-value	>0.05	>0.05	>0.05	>0.05	<0.05	>0.05	>0.05

a, b, c: values with different exponents are different at $p < 0.05$. Brand A: premium quality; brand B & C: medium quality; DM: Dry matter; CP: Crude protein; EE: Ether extract; CF: Crude fiber; NFE: Nitrogen-free Extract.

3.2. Evaluation of Preference Test Results with PCA

Principal component analysis (PCA) was performed on the preference test data to evaluate individual variability among cats and to identify potential outliers [32]. Most cats clustered close to one another during the PCAs, indicating similar consumption patterns across the tested diets. However, one individual was clearly separated from the main cluster in all PCA turns. The separation in all PCAs done with the data of the different food pairs indicated a markedly different preference behavior of that cat compared to the other subjects. Additionally, Mahalanobis distances were calculated for each cat, and the same cat was identified in the PCA score plots as having the highest distance based on the consumption data for bowls 1 and 2 and 1 and 3. Due to its strong deviation from the general pattern, that cat was identified as an outlier (see Figures S1–S3 in Supplementary Material) and excluded from subsequent statistical analyses to avoid bias in the interpretation of results [32].

3.3. Evaluation Based on Preference Ranking

The ranking reflects the relative preference of cats based on the percentage of food consumed during the preference test (Table 2). Brand A products were most preferred overall, with A-chicken showing the highest consumption (69.93%), indicating strong palatability [40]. Brand C ranked second, with moderate consumption values across its variants, particularly C-chicken and C-tuna. Brand B was the least preferred, as all its products recorded the lowest consumption percentages. The average consumption ratios of Brand A, B, and C were 42.31%, 23.05%, and 34.63%, respectively.

At the product level, chicken-based diets were generally more preferred than lamb and tuna, especially within Brand A and C. Conversely, all Brand B variants consistently ranked lower, suggesting reduced acceptability, possibly due to higher crude fiber content or less favorable texture. The average consumption ratios for chicken, tuna, and lamb flavors were 43.58%, 28.49%, and 27.94%, respectively.

Table 3 demonstrates the significance levels of group differences based on the cat food consumption. Pairs of brands are compared within each flavor, and pairs of flavors are compared within each brand [32]. The results confirm that there are more significant differences among brands within flavors than among flavors within brands.

Table 2. Preference ranking of cat food products.

Preference Ranking	Product	Consumed Food Ratio (%)
1	A-chicken	69.93
2	C-chicken	40.18
3	C-tuna	37.10
4	A-lamb	34.36
5	C-lamb	26.62
6	B-tuna	25.72
7	B-lamb	22.83
8	A-tuna	22.64
9	B-chicken	20.61

A: premium quality; brand B & C: medium quality.

Table 3. Level of significance of the differences between cat food consumptions (from Éles et al. [32]).

brands within flavors	A–B	B–C	A–C
chicken	0.000	0.000	0.000
lamb	0.019	0.475	0.126
tuna	0.610	0.000	0.000
flavors within brands	chicken-lamb	lamb-tuna	chicken-tuna
A	0.000	0.032	0.000
B	0.262	0.919	0.185
C	0.000	0.000	0.610

A: premium quality; brand B & C: medium quality.

3.4. Evaluation Based on EN Data

Canonical discriminant analysis (CDA) of the EN data was performed to discriminate cat foods according to both flavor and brand. The analysis showed that discrimination was primarily driven by brand, with brand-related differences exceeding flavor-related differences. Consequently, samples clustered more distinctly according to brand than according to flavor when all nine product groups were analyzed simultaneously (Figure 1). This observation does not imply the absence of flavor-specific odor characteristics. Rather, it indicates that the volatile profiles associated with different formulations and manufacturing practices within each brand contributed more strongly to the overall variation than the labeled flavor itself [34].

Flavor-related differences were nevertheless evident within individual brands. Even Brand B, which exhibited the most homogeneous odor profiles among its three flavors, showed measurable flavor-dependent separation by EN analysis. The flavor differences were even more pronounced in Brands A and C, indicating that the extent of flavor discrimination varied among manufacturers. Notably, the chicken-flavored product of Brand A, which also recorded the highest consumption in the preference test, was clearly separated along Function 1 (63.3% of the explained variance), reflecting a distinctive volatile profile. The discrimination performance of the EN model was further supported by the group distances and cross-validation results presented in Figure 2, confirming that flavor-related volatile differences were detectable despite the stronger influence of brand-specific formulation and processing characteristics. These findings further demonstrate the potential of EN technology for characterizing aroma profiles and differentiating commercial pet foods, consistent with previous reports on its application in the pet food industry [41].

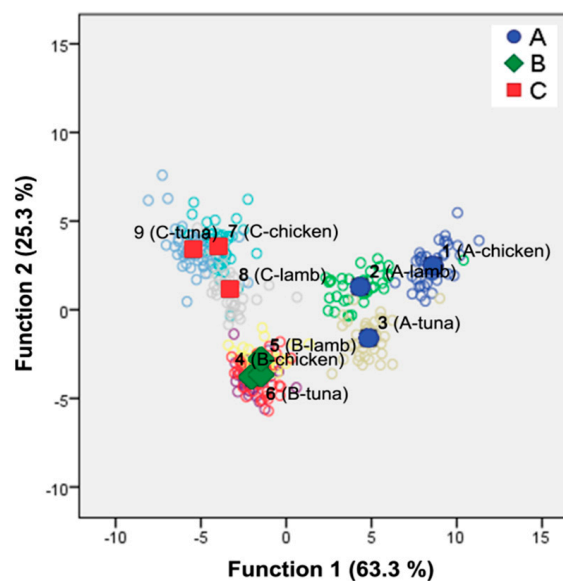


Figure 1. Separation of cat food groups in canonical discriminant analysis was calculated on electronic nose data to identify flavors and brands [34]. (A: premium quality; B & C: medium quality; in brackets on axes: the percentage of the total variance of the original electronic nose sensor signal data (digital aroma fingerprint) explained by the respective discriminant function).

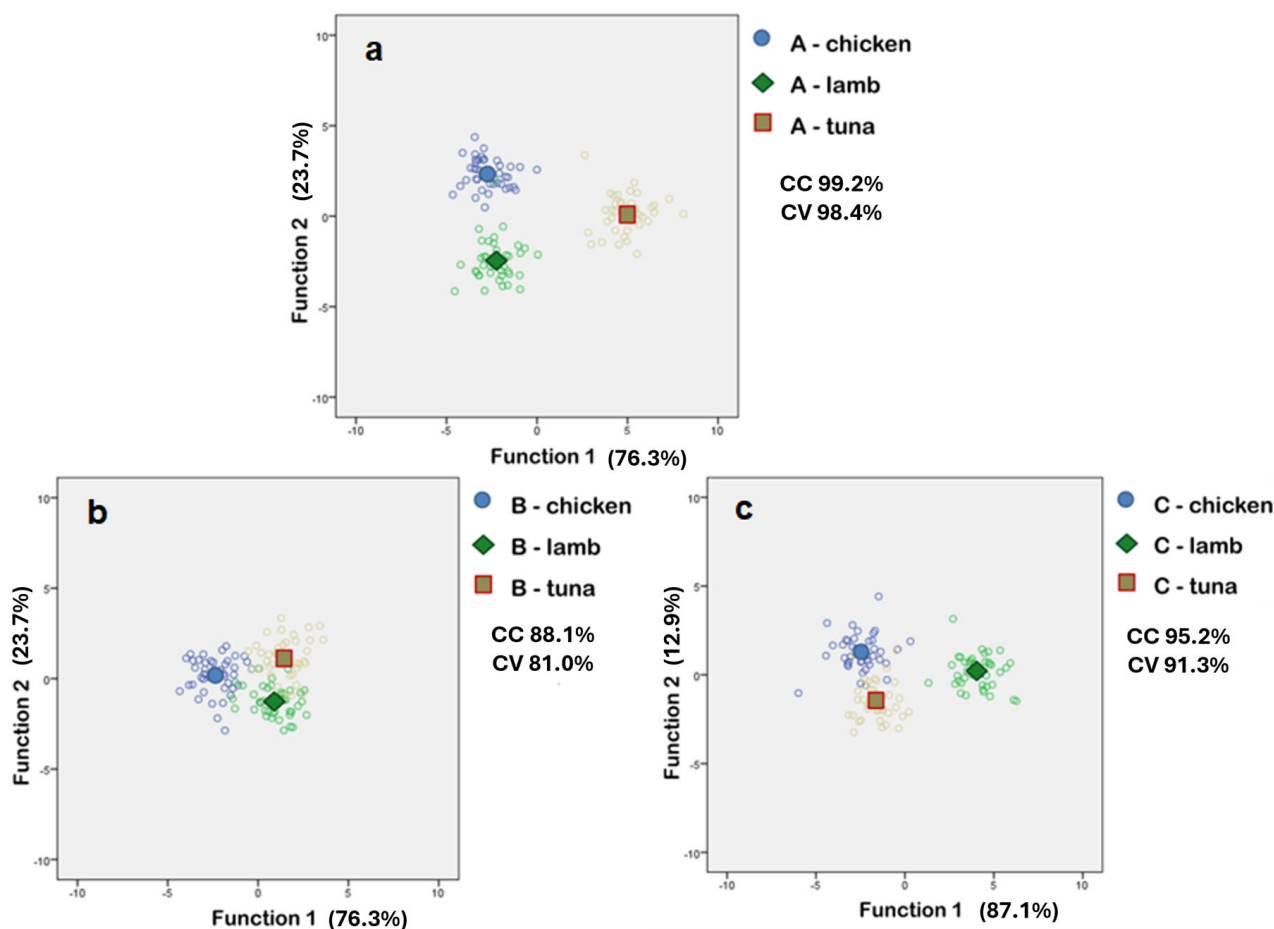


Figure 2. Results of discriminant analyses of aroma profiles of cat food variants by flavor within (a) brand A, (b) brand B, and (c) brand C, indicating the hit rate in calibration and cross-validation (A: premium quality; B & C: medium quality; in brackets on axes: the percentage of the total variance of the original electronic nose sensor signal data (digital aroma fingerprint) explained by the respective discriminant function; CC: classification calibration; CV: cross-validation).

3.5. Comparison of EN Results with the Preference Test

Compared with the preference ranking (Tables 2 and 3), the electronic nose discriminant analysis (DA) shows a consistent pattern in differentiating the cat food samples according to brand and likely palatability. In the preference test, Brand A was most preferred, followed by Brand C, while Brand B was least preferred. This trend is reflected in the DA plot, where Brand A samples are clearly separated and clustered on the positive side of Function 1, indicating a distinct and potentially more attractive aroma profile. Brand C samples occupy an intermediate position, aligning with their moderate consumption levels, while Brand B samples cluster separately in a lower region, corresponding to their lower preference.

Again, highly consumed items such as A-chicken are positioned distinctly from low-ranked products like B-chicken and B-lamb, suggesting that differences in volatile compounds may underpin preference [42]. The DA supports the preference results, indicating that aroma characteristics are closely associated with consumption and acceptability in cats.

3.6. Evaluation of Individual Brands Based on EN Data

The discriminant analysis (DA) (Figure 2) plots illustrate the separation of chicken, lamb, and tuna variants within each brand based on their volatile aroma profiles. For Brand A (Figure 2a), clear and well-defined clustering is observed with minimal overlap, supported by high classification (CC: 99.2%) and cross-validation (CV: 98.4%) accuracies, indicating strong differentiation among flavors. Brand B (Figure 2b) shows less distinct separation with noticeable overlap between clusters and lower classification performance (CC: 88.1%; CV: 81.0%), suggesting more similar aroma profiles among its variants. In contrast, Brand C (c) demonstrates good separation of samples with high classification accuracy (CC: 95.2%; CV: 91.3%), although slight overlap is present.

The results indicate that aroma profiles are most distinct in Brand A, moderately distinct in Brand C, and least differentiated in Brand B, which may contribute to differences in product preference.

The reason for applying leave-one-day-out cross-validation was to test the effect of the drift of MOS sensors of the EN. As CV results were close to 100%, the drift caused by doing the measurements over the 10 days was not influential [43].

The discriminant analysis (DA) plots (Figure 3) demonstrate clear separation of cat food samples by brand (A, B, and C) within each flavor category (chicken, lamb, and tuna), based on their volatile aroma profiles. For all three flavors, distinct and non-overlapping clusters are observed, indicating strong differentiation among brands. High classification (CC = 100%) and cross-validation (CV = 99.2–100%) accuracies confirm the robustness and reliability of the model. Function 1 explains the majority of variance (61.2–79.6%), highlighting its primary role in discriminating samples. Brand A samples are consistently separated from Brands B and C, while Brands B and C also form distinct clusters. This indicates that each brand possesses a unique aroma signature regardless of flavor type.

There are similarities in the trends of the average group differences in flavors within brands, and those of the brands within flavors, measured in the preference test or in the electronic nose tests (Table 4): (i) The three flavors of brand A showed the largest differences in the preference test, while the flavors of brand B were the most homogeneous. (ii) The biggest difference between the three brands was found in the case of chicken flavor, in other words, chicken flavor showed the biggest variation among the brands, while the smallest brand-based variation was found in the case of lamb flavor. The same trends were found based on the electronic nose measurements in both comparisons.

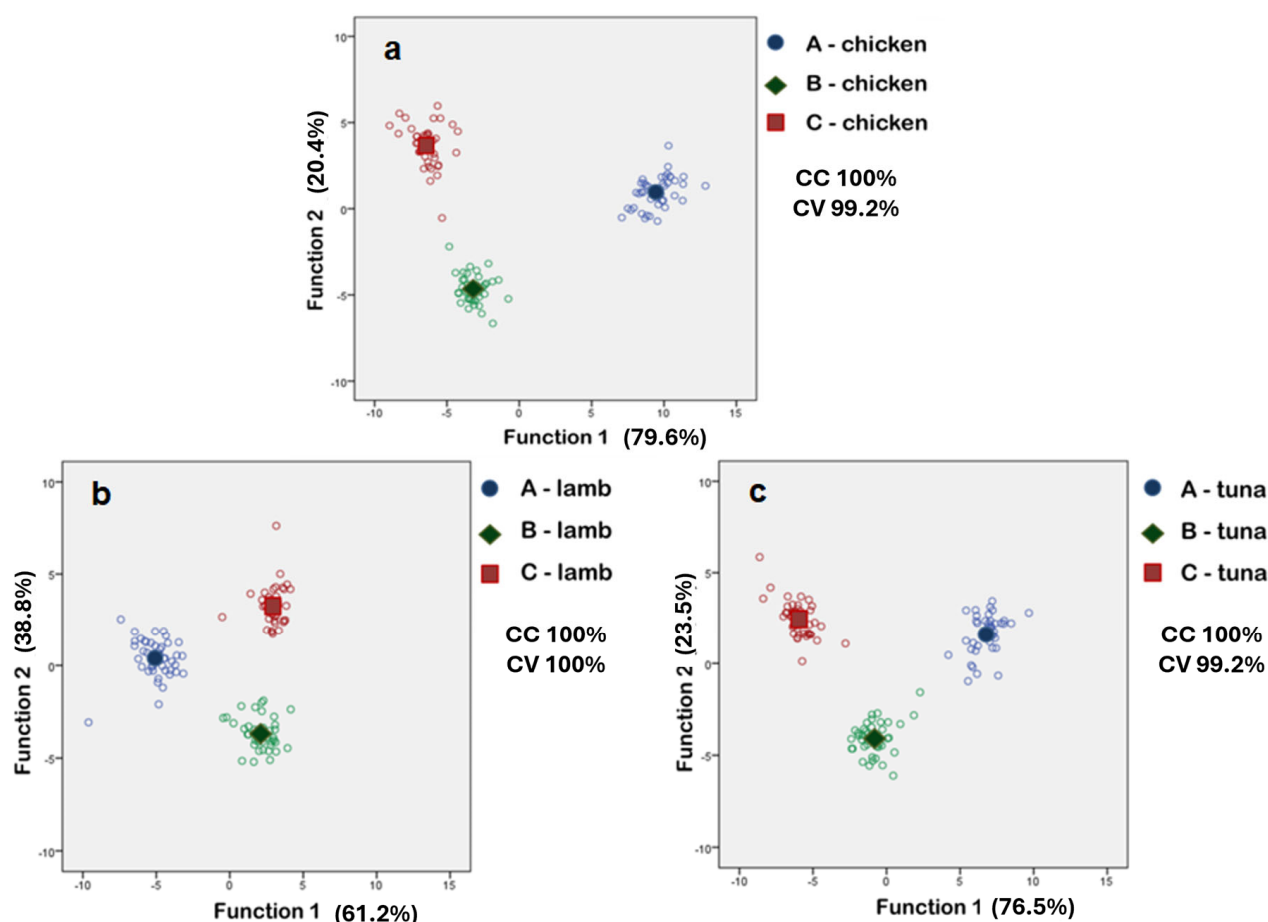


Figure 3. Results of discriminant analyses of aroma profiles of cat food variants by brands within (a) chicken, (b) lamb, and (c) tuna flavors, indicating the hit rate in calibration and cross-validation (A: premium quality; B & C: medium quality; in brackets on axes: the percentage of the total variance of the original electronic nose sensor signal data (digital aroma fingerprint) explained by the respective discriminant function; CC: classification calibration; CV: cross-validation).

Table 4. Trends of group distances measured during the preference test and the electronic nose measurements.

Groups Between Which the Distance is Measured	Average Difference in Consumed Food Ratio (Based on Table 2)	Average Centroid Distances in Electronic Nose-Based Discriminant Analysis
3 flavors of brand A	31.53	6.8 (see Figure 2a)
3 flavors of brand C	9.04	5.1 (see Figure 2c)
3 flavors of brand B	3.41	3.3 (see Figure 2b)
3 brands of chicken flavor	32.88	12.9 (see Figure 3a)
3 brands of tuna flavor	9.64	10.2 (see Figure 3c)
3 brands of lamb flavor	7.69	7.9 (see Figure 3b)

Both in the preference test and in EN-based aroma evaluation, the differences among brands within single flavors were larger than the differences among flavors within a single brand. This was confirmed by the cross-validation hit rates of DA, which remained 99% in the brand classifications (Figure 3), while declining in the flavor classification (Figure 2).

It is important to emphasize that the DA in this study was employed strictly as a descriptive exploratory tool rather than a predictive framework for external samples. While PCA captures the dominant global variances within the dataset, DA was specifically utilized to isolate group-dependent variances and detect minute, systematic multivariate differences

among the product profiles. Because our dataset consists of repeated longitudinal measurements of nine specific commercial products, the high classification accuracies demonstrate successful group characterization and tool reliability against daily drift, rather than generalizable predictive performance on independent commercial batches. Consequently, future studies incorporating distinct manufacturing lots would be necessary to transition this descriptive approach into a prospective predictive quality control application.

The results demonstrate the descriptive capacity of the applied gas-sensor-based EN system as an objective analytical tool for characterizing commercial cat food profiles. Our findings indicate that the EN-based discriminant analysis—specifically through the evaluation of average centroid distances—effectively mirrors the grouping patterns observed in long-term animal preference trials based on average consumed food ratios. The comparative evaluation of this study was intended as a descriptive approach rather than a quantitative predictive framework. Rather than establishing a direct mathematical prediction model, our objective was to evaluate how closely the instrument-derived grouping of cat foods aligns with the behavioral grouping generated by long-term consumption data. The strong qualitative and numerical alignment between the structural distances in the EN data and the animal preference metrics underlines the potential of the EN system to serve as a reliable, welfare-friendly descriptive surrogate for screening dietary aroma profiles before initiating resource-intensive animal testing.

4. Conclusions

The study demonstrated that cat food preference is influenced more by physicochemical and sensory-related factors than by basic macronutrient composition. Although most proximate analysis parameters did not differ significantly among brands, crude fibre content showed differences and it was a determinant of palatability. EN analysis revealed clear brand- and flavor-specific differences in volatile profiles, which aligned well with preference rankings, indicating that aroma significantly contributes to acceptability.

Additionally, discriminant analysis confirmed strong differentiation among brands and, to a lesser extent, among flavors. Overall, the integration of preference testing, physicochemical analysis, and electronic nose data provides a comprehensive understanding of factors influencing cat food acceptance, highlighting the importance of formulation quality, aroma, and texture in product development. Further investigations are required to evaluate preference tests in detail and to uncover closer relationships between animal preferences and EN measurements.

In conclusion, the findings of this study demonstrate that the aroma fingerprints of cat foods described by the applied gas-sensor-based EN system are closely related to the preference of cats measured during feeding trials. While the longitudinal study of nine products serves as a descriptive evaluation of instrumental stability against drift rather than a prospective predictive model for independent commercial batches, the clear alignment between instrument-derived centroid distances and animal consumption ratios confirms the high descriptive capacity of this approach. Once calibrated and validated, the EN system can serve as a rapid, objective, and sustainable quality control tool, providing a welfare-friendly alternative or complementary descriptive surrogate to traditional animal preference trials by identifying aroma profiles linked to highly accepted commercial diets.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/chemosensors14080180/s1>, Figure S1: PCA with preference data (consumption %) for bowls 1 and 2; Figure S2: PCA with preference data (consumption %) for bowls 2 and 3; Figure S3: PCA with preference data (consumption %) for bowls 1 and 3.

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Abbreviations

The following abbreviations are used in this manuscript:

CC	Classification Calibration
CV	Cross-validation
DA	Discriminant analysis
EN	Electronic nose

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