Preference prediction modeling for coffee beverages by integrating the CATA method with E-Nose and E-Tongue

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Introduction and Objectives

It is important to base product development on consumer preferences. Nevertheless, time and money, which are crucial factors in corporate activities, are often wasted on excessive consumer research for selecting prototypes; in contrast, neglecting such research may lead to the market launch of compromised products. This study aims to construct a 'preference prediction model' for ready-to-drink (RTD) coffee beverages. The goal is to simplify the construction of a prediction equation by correlating data from a single consumer survey with statistically processed data. This is accomplished using a rapid sensory evaluation method, known as Check-All-That-Apply (CATA), and analytical equipment such as Electronic Nose (E-Nose) and Electronic Tongue (E-Tongue).

Materials and Methods

1. Consumer survey

(1) Panelists

・110 consumers (77 males, 33 females, ages 20s-50s)

(2) Test items

・CATA questionnaire: 25 terms selected by 10 consumers
・Preference score: 7-point hedonic scale of liking/disliking

(3) Survey schedule

・All panelists participated in CLT over two consecutive days

(4) Sample

・ 15 RTD coffee beverages containing milk and sweetener

(5) Evaluation method

・FIZZ (Biosystemes) was used for evaluation design and data tabulation
・Samples were served monadically

Table 1. CATA terms of RTD coffee beverages containing milk and sweetener

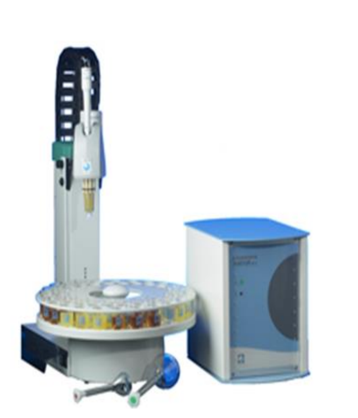
Flavor (13)	Milky (F)	Sweet (F)	Sour (F)	Bitter (F)	Astringent (F)	Roasted (F)	Citrus (F)
	Artificial (F)	Fresh cream (F)	Bitter chocolate (F)	Milk tea-like (F)	Caramel-like (F)	Well balanced (F)	
Mouth Feel (4)	Light (M)	Heavy (M)	Smooth (M)	Viscosity (M)			
Aftertaste (8)	Sweet (A)	Milky (A)	Bitter (A)	Astringent (A)	Sour (A)	Coffee Remain (A)	Light (A)
	Long (A)						

2. E-Nose, E-Tongue

Same 15 samples as the consumer survey were measured.

E-Nose：HeraclesⅡ (Alpha M.O.S)
The GC instrument featured two columns with different polarities mounted in parallel and coupled to two FIDs. The GC is also equipped with an automatic purge-and-trap system to improve sensitivity. Analyzing the headspace vapor of 10g-sample with 1.5g-NaCl from incubated in a vessel at 80℃.

E-Tongue: Astree (Alpha M.O.S)
The samples were reacted with 7 types of sensor arrays with different specificities for 2 minutes, and the potential difference between the Ag/AgCl electrode and each sensor was measured. All samples (N=2) were analyzed as undiluted solution.



3. statistical analysis

The statistical analysis software XLSTAT Sensory (Addinsoft) was used.

Results

I. Analysis of Consumer Survey Data

- CATA data were used for correspondence analysis (CA) to find relationships between samples and terms.
- Agglomerative Hierarchical Clustering (AHC) based on preference scores classified consumers into three groups.

Cluster1; Coffee liker
Cluster2; Milk, sweetness liker
Cluster3; RTD coffee lover

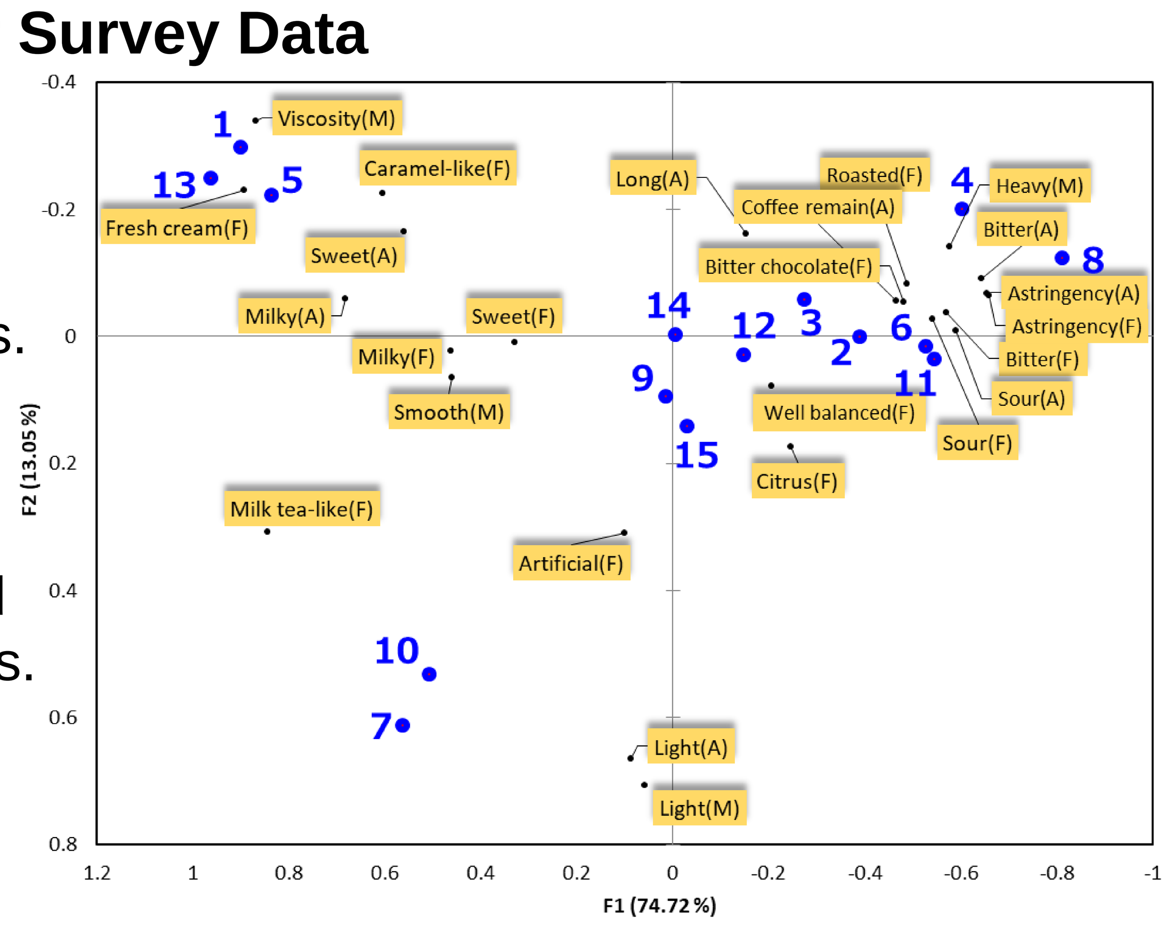


Fig 1. Results of CA by CATA

II. Correlation between sensory evaluation and E-Nose, E-Tongue

- The data of E-Nose and E-Tongue with high correlation of CATA-CA were extracted, and principal component analysis (PCA) was performed.
- The CA and the PCA showed an excellent correlation (RV = 0.784, p = 0.001).

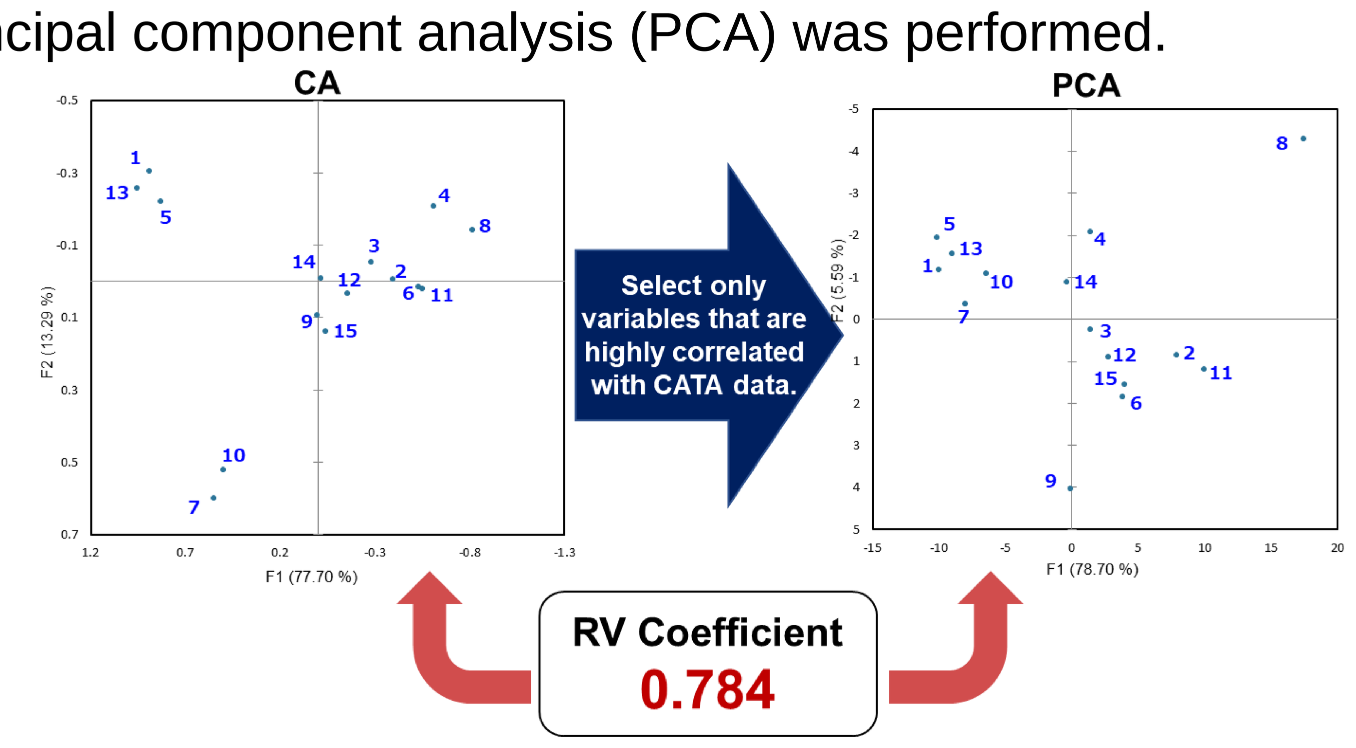


Fig 2. RV coefficient between CATA-CA and PCA with E-Nose and E-Tongue

III. Preference Mapping (PREFMAP) by Preference Cluster

- PREFMAP established model equations about the distribution of preferences for each cluster on the PCA with E-Nose and E-Tongue. Predictive score was calculated using each equation.

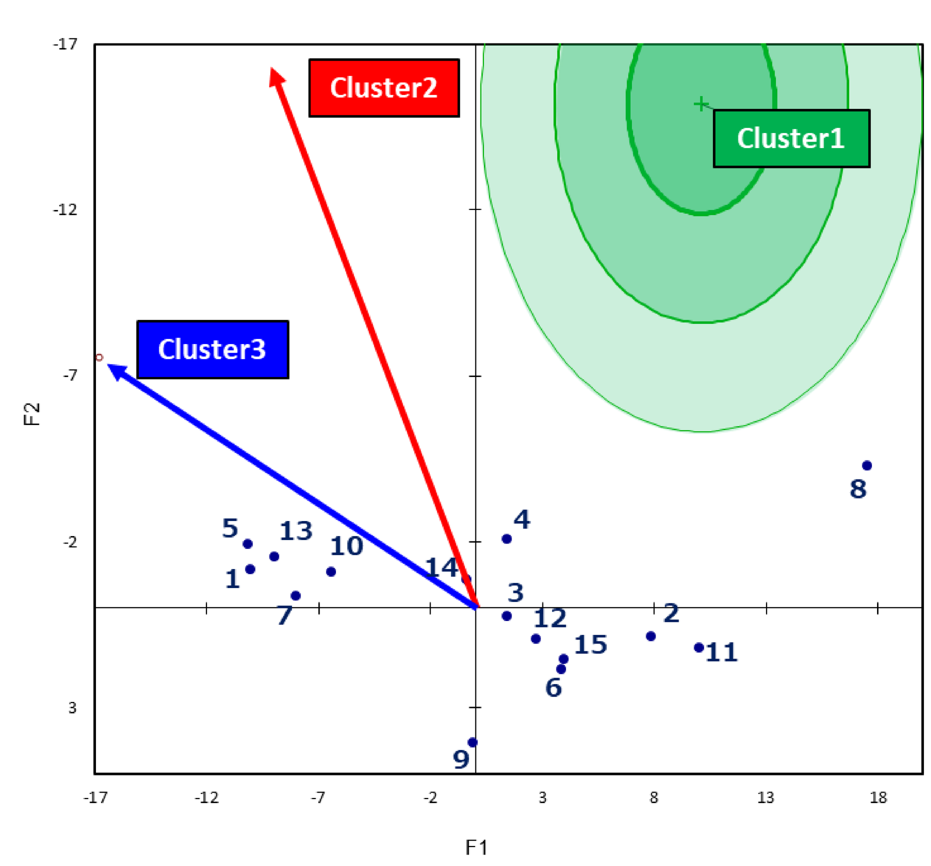


Fig 3. PREFMAP obtained from E-Nose, E-Tongue data and preference scores, and model equations for each cluster

Fig 4. Comparison of actual score and predictive score from model equations for each cluster (7; Like Extremely 6; Like Moderately5; Like Slightly 4; Neither Like nor Dislike 3; Dislike Slightly 2; Dislike Moderately 1; Dislike Extremely)

Table 2. Model equations for each cluster

Y	intercept	F1	F2	F1^2	F2^2
Cluster1	4.805	0.082	-0.123	-0.004	-0.004
Cluster2	4.377	-0.030	-0.053	0.000	0.000
Cluster3	5.497	-0.037	-0.017	0.000	0.000

Table 3. Deviation from actual score

	min	max
Cluster1	0.05	0.79
Cluster2	0.02	0.92
Cluster3	0.00	0.69

Conclusion

This study results in the construction of a model that can predict preference scores by combining consumer survey data with instrument analysis data. Furthermore, the use of rapid methods like CATA, E-Nose, and E-Tongue is considered highly beneficial from the standpoint of time and cost savings.

Discussion

The preference prediction scores calculated by the model show a minor deviation from the actual values of the samples. It is necessary to consider refining the instrument analysis method to improve the correlation with the sensory evaluation data gathered from the survey.

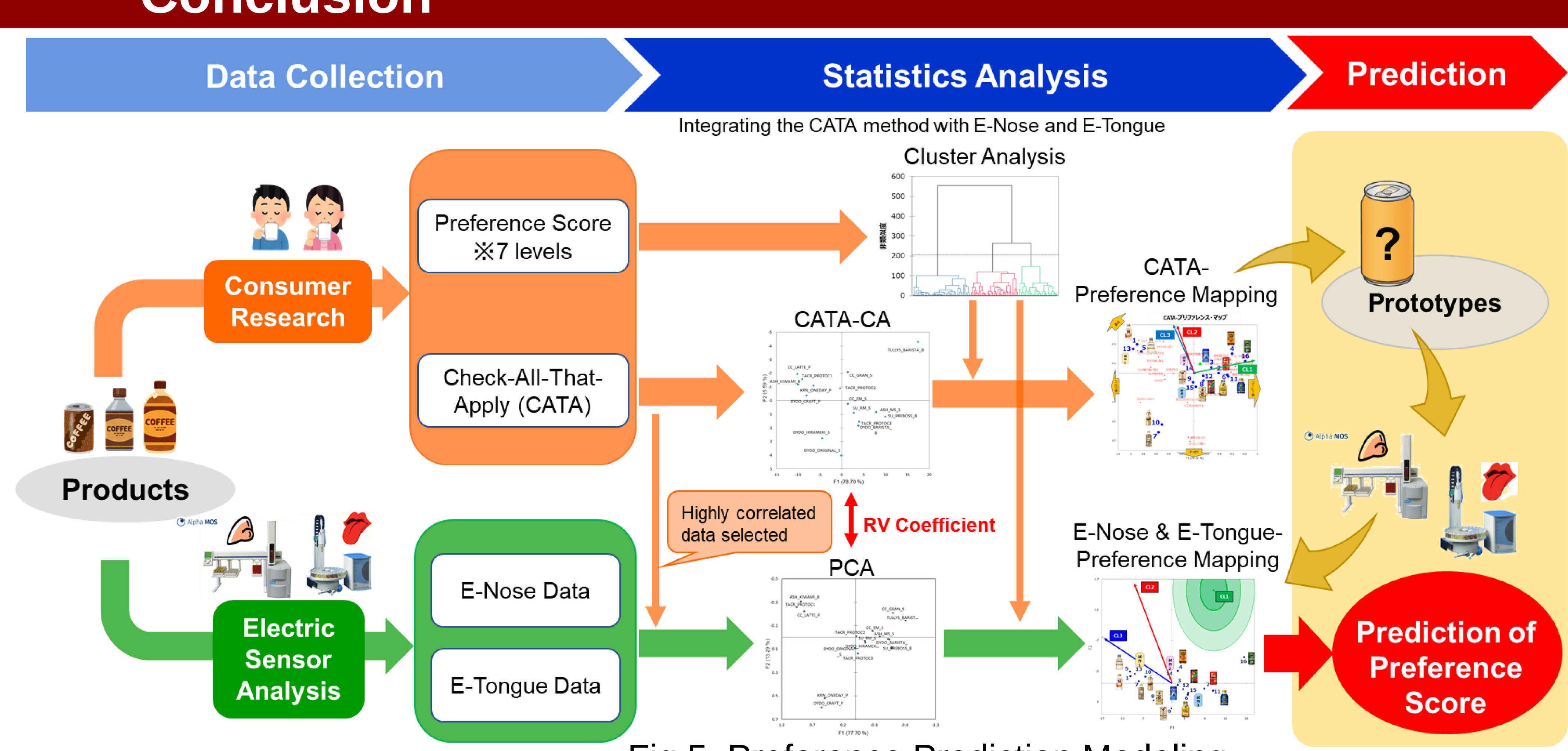


Fig 5. Preference Prediction Modeling