Sensitivity Analysis of Temporal Sensory Responses on Preference: Application to Coffee

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***Abstract*—Understanding how the temporal evolution of sensory attributes influences consumer preference is critical for enhancing user experience in the field of consumer electronics. This study proposes a sensitivity analysis framework that models time-series liking scores based on Temporal Dominance of Sensations (TDS) data. Reservoir computing, a recurrent neural network technique well-suited for time-dependent data, was used to train models predicting Temporal Liking (TL) curves from TDS inputs. The sensitivity of each sensory attribute was quantified by applying step inputs for individual attributes and measuring the maximum values of the predicted TL curves. The framework was evaluated using coffee-tasting experiences. The results revealed that attributes such as rich/deep and roasted reasonably exerted stronger effects on liking compared to other attributes. These findings provide valuable insights for designing products that optimize consumer satisfaction.**

***Index Terms*—Temporal Dominance of Sensations, Temporal Liking, reservoir computing**

I. Introduction

Temporal Dominance of Sensations (TDS) is a widely used method for capturing the dynamic evolution of sensory perceptions during an experience [1], [2], while Temporal Liking (TL) method [3] records consumers' moment-to-moment preferences over time. Linking data obtained from these two methods is essential for understanding how consumer preferences are shaped by their evolving sensory experiences with products or services [4].

In our previous work, we applied sensitivity analysis to time-series liking scores of strawberries using reservoir computing, demonstrating how sensory attributes influence preference formation [5]. However, to demonstrate the generalizability of the approach, it is necessary to apply the method to other types of stimuli.

In this study, we focus on coffee as the target stimulus, given the well-established TDS protocols for food products. The data were originally collected in our earlier study [6]. Nevertheless, both TDS and TL methods can be extended to broader consumer experiences, including video viewing and gameplay [7]–[9]. Sensitivity analysis thus holds promise as a general framework for investigating how dynamic sensory responses influence consumer preference across diverse product categories.

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II. Temporal Dominance of Sensations Method

The TDS experiment was conducted using a computer application with multiple buttons labeled with sensory attributes. Experimental participants (panelists) took a sip of coffee and then initiated the task [6]. While tasting the coffee, panelists pressed the button corresponding to the attribute they perceived as most dominant. Only one button could be selected at any given time. Panelists switched to a different button as soon as their dominant sensation changed. There were no restrictions on how often attributes could be selected; instead, the system continuously recorded the currently selected attribute throughout each 15-second session.

After ten seconds, participants swallowed the coffee but continued the task for an additional five seconds to report lingering flavors. The total task duration was set to 15 s (10 s for tasting and 5 s for lingering flavors). This duration was determined through preliminary discussions among the authors. Since beverages such as coffee are consumed at different speeds depending on individual habits, we adopted a fixed time window to minimize inter-individual differences in tasting duration.

The results of the TDS method were visualized as temporal evolution curves. A curve for each attribute shows the time-series changes in its dominance proportion, which is defined as the proportion of panelists selecting that attribute at a given time point. The time axis was normalized from 0 (initiation of the task) to 1.0 (end of the task). TDS curves depict the average sensations across all panelists.

III. Temporal Liking Method

As with the TDS method, the TL experiment was conducted using a computer application. The interface consisted of nine buttons labeled from 1 to 9. While tasting the coffee, panelists pressed the button corresponding to their level of preference, selecting 9 for a very favorable impression and 1 for a very unfavorable impression. The timing for swallowing the coffee and ending the task was identical to that of the TDS task.

The TL curve represents the time-series changes in the average liking score. In this study, the liking score ranged from 1 to 9. However, during the initial period before the first button was pressed, the score was set to 0 in the TL curve. As with the TDS curves, the time axis was normalized from 0 (initiation of the task) to 1.0 (end of the task).

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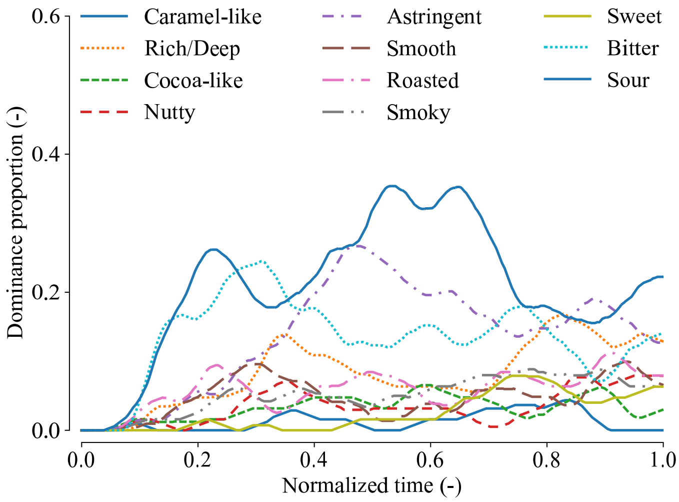

Fig. 1. TDS curves of Columbia brand coffee.

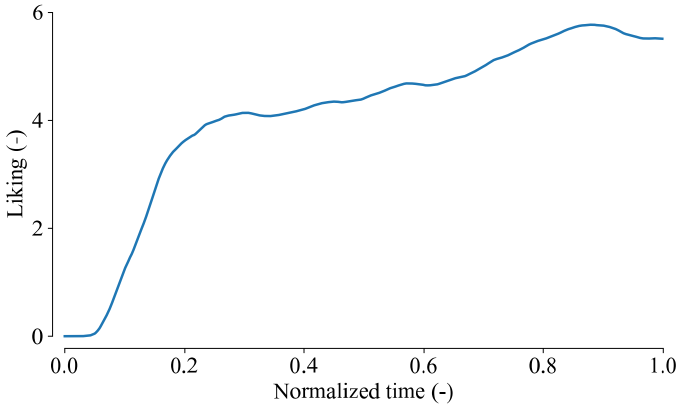

Fig. 2. TL curve of Columbia brand coffee.

IV. TDS/TL Dataset of Coffee Products

In this study, we used the TDS/TL dataset of coffee products obtained in our previous study [6]. Eleven attributes were originally adopted, however, this paper focuses on the six most prominently selected attributes: astringent, bitter, rich/deep, roasted, smooth, and sour. The dataset contains TDS/TL curves for four brands of coffee, but in this study, we do not distinguish these products. Thus, we have 48 TDS/TL curves (21 panelists $\times$ 4 products). Figs. 1 and 2 show the TDS and TL curves of Columbia brand in this dataset.

V. Sensitivity Analysis

To model the relationship between TDS and TL curves, we employed reservoir computing [10], [11], a machine learning technique based on recurrent neural networks that is well-suited for time-series data. The reservoir size, i.e., the number of neurons in the reservoir, was set to 128. The input scaling factor was fixed at 1.0, and the leak rate was set to 0.01. Spectral radius was set to 0.9. These values were selected based on preliminary experiments that balanced model performance and stability [5].

TABLE I
Sensitivities for six attributes with 95% confidence intervals.

Attribute	Sensitivity
Rich/Deep	7.32 ± 1.55
Roasted	7.04 ± 1.09
Bitter	5.81 ± 1.33
Sour	4.96 ± 0.43
Astringent	4.29 ± 0.82
Smooth	4.15 ± 1.16

A pair of TDS and TL curves from the same panelist is referred to as a "curve set." From the original 48 curve sets, 100 resampled TDS and TL curves were generated using bootstrap resampling [12]–[14]. These were used to train the reservoir computing model. This procedure was repeated 16 times to construct 16 models, enabling the estimation of confidence intervals for the sensitivity values. While there was no strict theoretical requirement for this specific number, we selected 16 repetitions as a practical compromise, which allows for the computation of meaningful confidence intervals.

For each trained model, a sensitivity test was conducted by providing a step input for each sensory attribute. A step input refers to a TDS curve in which the target attribute maintains a constant value of 1 throughout the entire time period, while all other attributes are set to 0. The maximum value of the TL curve predicted in response to this input was defined as the sensitivity of the corresponding attribute. Sensitivities for six sensory attributes were computed across the 16 models.

VI. Results

The computed sensitivities are shown in Table I with 95% confidence intervals calculated across the 16 models to estimate the variability in sensitivity scores. Rich/deep exhibits the highest sensitivity, indicating that this attribute had the strongest effect on the liking score among all six. In contrast, smooth exhibits the lowest sensitivity.

VII. Discussion

Rich/deep and roasted showed highest sensitivities, suggesting that these attributes have a stronger positive influence on the liking of coffee. This is consistent with the general understanding that richness and roasted flavor are desirable characteristics in coffee [15], [16].

On the other hand, attributes such as astringent and smooth exhibited lower sensitivities. Astringency is generally preferred by individuals who enjoy coffee [17], [18]. Since all panelists in the present study were coffee drinkers, the low sensitivity to astringency cannot be easily explained. Regarding the smooth attribute, few comparable studies are available in the literature, making it difficult to assess the validity of this result.

The relatively moderate sensitivity of bitter and sour reflects the complexity of individual preferences regarding these attributes, as bitterness and sourness can be perceived either positively or negatively depending on context and personal preference [16], [19].

The sensitivity analysis conducted for strawberries in our previous work [5] yielded interpretable and reasonable results. While the present findings for coffee highlight the potential of data-driven sensory analysis, further validation is still required.

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