PhD THESIS

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Integration of psychophysical answers to sensory evaluation systems of food

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1. BACKGROUND AND OBJECTIVES

My scientific objectives

Developing new sensory methodologies to eliminate the confounding effects present and derive higher quality results that better describe reality.

Sub-objectives

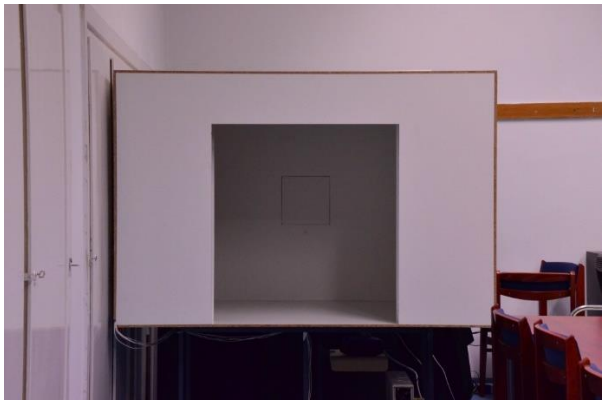
1. I aim to compare the different visual masking methods used in sensory testing and, based on these, to implement effective color masking of different food product groups.
2. In cross-modal perception, information coming in through the sensory channels (sight, smell, taste, touch, and hearing) interacts with each other. I aim to investigate the cross-modal effects of different colored light environments on chocolate bars.
3. I aim to develop an instrumental method of color determination for beers, adapted to human color perception, which will allow further objective and detailed characterization of beers.
4. I aim to identify parameters suitable for comparing difference analysis methods and to develop a multicriteria decision support system for comparing difference analysis methods.
5. I aim to create an electroencephalographic (EEG) experimental environment and develop a test and evaluation system to study the effects of food flavor aroma stimuli.
6. I aim to compare the channel signals (delta, theta, alpha, beta, gamma) elicited by the olfactory stimulus and the reference. I also aim to assess the effects of mood, fatigue and odor sensitivity and to explore patterns between EEG signals.
7. I aim to develop a trained and tested neural network model that can classify olfactory stimuli based on EEG signals.

2. MATERIALS AND METHODS

The sensory experiments were carried out at the Sensory Laboratory of the Institute of Food Science and Technology of the Hungarian University of Agricultural and Life Sciences. The experiments in the light booth were carried out at the Department of Mechatronics, Optics and Mechanical Engineering Informatics of Budapest University of Technology and Economics.

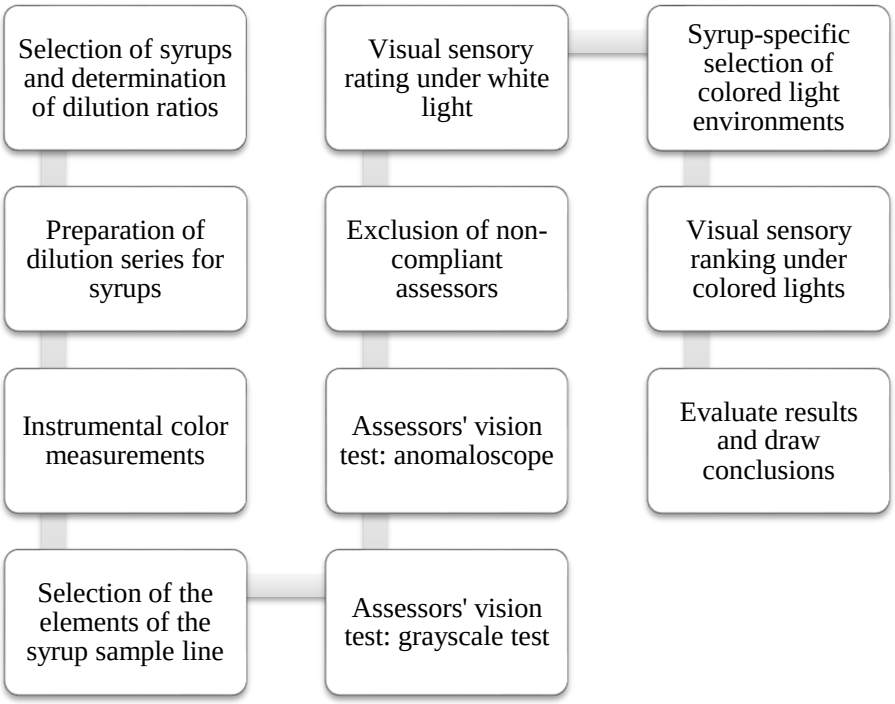
2.1 Spectrally tunable lighting booth

In order to avoid color masking inaccuracies, a spectrally tunable measuring station (hereafter referred to as "light booth") of our own design was built, in which illuminations of any color can be easily and accurately adjusted. The rectangular installation measures 1.5 x 1 x 1 m and contains 5 different types of LEDs (red, blue, green, white and amber) mounted on 4 fixed panels. The LEDs are installed in the corners of the cabin, one on each vertical panel, so that the direct light from the diodes is projected onto the white walls, and thus the emitted light is reflected back into the working space after multiple reflections. The light box is accessible through an opening in the front surface. The cabin provides a spacious and comfortable working space for the assessor. A key design consideration was to position the panels so that the light density is evenly distributed over both the horizontal bottom surface and the walls. The system is controlled by two Arduino Uno microcontrollers. The luminous flux of the LED channels can be set to relative control values ranging from 0-255, based on which the microcontroller implements pulse width modulation to achieve illumination. The brightness of the diodes is adjusted by varying the fill factor.



1. Figure: Exterior view of the light box

2.2 **Syrups**



2. Figure: Flowchart for the syrup experiment

In this research, the main question was that which colored light environments were best suited for masking different colored syrup sequences. For the study, I used four distinctly colored syrups: yellow (Ági Citrus mix syrup), blue (Pölöskei Blue raspberry syrup), green (Auchan Kiwi fruit syrup) and red (Red Riding Hood raspberry syrup). For each color, 10-member dilution series with pre-fixed ratios (1:4; 1:5; 1:6 ... 1:13) were prepared, from which a 5-member sample series was selected after instrumental color measurement. The selection was based on the ΔE^*_{ab} value indicating the degree of color difference. In the selection process, an attempt was made to approach ΔE^*_{ab} =2 in all cases. After preparation, the samples were stored in sealed containers and presented to the assessors in transparent glass beakers.

Prior to the sensory evaluation the color vision of the prospective assessors were tested using an anomaloscope (OCULUS 47700 Heidelberg MultiColor anomaloscope) and a greyscale test. The color of the drink samples was determined using a handheld tristimulus colorimeter (X-rite RM200QC). The aim of the sensory test was to investigate the effect of masking lights. For this purpose, the assessors had to rank the syrups according to their hue. In the end, 14 assessors, who were proven not to be color deceivers, participated in the test. The sensory assessment was carried out in two steps, and in both cases, the correctness and the time of the ranking were monitored. In the first step, the reference measurement was performed, i.e. the assessors had to

sort the syrup samples according to their hue under artificial sunlight. In the second step, the assessors performed the same task under colored light conditions.

In the experiment, 4-4 different colored light environments were defined for each syrup sample series: the assessors tested each sample series in Blue (Light1) and Red (Light2) light environments, and the other two color combinations were determined in a preliminary test, in which two more specific color environments were defined based on the color of the sample series.

1. Table: Illumination environments used for each syrup (percentage values, i.e. what percentage of the LED was lit compared to its maximum output)

Ratio of LEDs	Red syrup				Green syrup			
	Light1	Light2	Light3	Light4	Light1	Light2	Light3	Light4
red	0	**100**	**100**	**80**	0	**100**	0	**50**
green	0	0	0	**10**	0	0	**80**	**80**
blue	**100**	0	**100**	**10**	**100**	0	**10**	**10**
amber	0	0	0	0	0	0	**10**	0
Ratio of LEDs	Blue syrup				Yellow syrup			
	Light1	Light2	Light3	Light4	Light1	Light2	Light3	Light4
red	0	**100**	**100**	0	0	**100**	0	0
green	0	0	0	**100**	0	0	0	**50**
blue	**100**	0	**100**	**100**	**100**	0	0	0
amber	0	0	0	0	0	0	**100**	**50**

I evaluated the correctness of the rankings using the Page test and the Cabilio-Peng pairwise comparison, and the time data using Kaplan-Meier survival analysis.

2.3 **Chocolates**

In this experiment the masking of a series of milk chocolate bars was tested using a tunable light booth. The lightest member of the 10-member series contained 3.00% cocoa powder, while the darkest contained 9.75% cocoa powder (with uniform increases of 0.75%). The colors of each chocolate were determined using a tristimulus colorimeter (X-rite RM200QC), and spectral measurements were also made (Konica Minolta CM-2600d spectrophotometer, 360-740nm, 10 nm resolution) to design appropriate masking lighting. Out of the 10 chocolates a 5-element series with a color difference (ΔE_{ab}) between members of the series between 2.0 and 3.0 ("noticeable difference") was selected. The assessors' vision was investigated by an OCULUS 47700 Heidelberg MultiColor anomaloscope. Sensory assessors who passed the screening tests were asked to rank the chocolate samples from lightest to darkest under artificial sunlight and then under different colored illuminations. In Experiment 1, assessors performed visual sensory tests under

four different monochromatic lighting conditions (Red, Green, Blue and Amber). In Experiment 2, assessors evaluated chocolate samples under a specific combination of previously applied lights. The rankings were also performed on scaled data (relative to their own time score) to eliminate systematic error due to variability in the assessors' individual judgment time.

2.4 Cross modal effects (chocolates)

In this experiment the effects of color masking lights on changing non-visual sensory (cross-modal) parameters were tested. For this purpose, we produced chocolate samples with specific recipe, in which two parameters were systematically varied: the sweetener (sugar or maltitol) and the cocoa powder content. We produced 6 different chocolate samples, 3 with sugar and 3 with maltitol. The 3-3 chocolate samples had a cocoa solids content of 50%, 60% and 70%. Therefore 6 samples were produced, which had differences in exactly two parameters. The ones with sugar were signed as 50C, 60C and 70C, and the ones with maltitol were named as 50M, 60M and 70M according to their cocoa content.

In the first step, the color vision of the selected assessors was tested with an OCULUS 47700 *Heidelberg MultiColor* anomaloscope. In the second step, the hue of the chocolates was evaluated under artificial sunlight (D65) in a tetrad test. In the third step, the assessors evaluated the chocolates under white (D65) light, in which they had to rate the pre-fixed properties of the chocolates on a 20-item scale. In the fourth step, the assessors examined the chocolates under colored light environments (blue, red, green, amber and orange) in a similar way to the third step.

2.5 Beers

The aim of the experiment with beers was to find out whether the EBC color system in force is suitable for accurately and objectively determining the color of all commercially available beers. 39 different beers were tested for the study. We investigated three Alcohol-free pale lagers, three Alcohol-free beer based mixed drinks, three Beer-based mixed drinks, two Strong pale lager, nine European pale lagers, two Czech pilsners, one American adjunct lager, two Schwarzbier, one Stout, one Irish stout, one Altbier, four Weissbier (unfiltered wheat beer), one International amber lager, one Belgian strong pale ale, one Irish red ale, one Dunkles bock and three Specialty fruit beers. With this data selection we aimed to involve many types of beer.

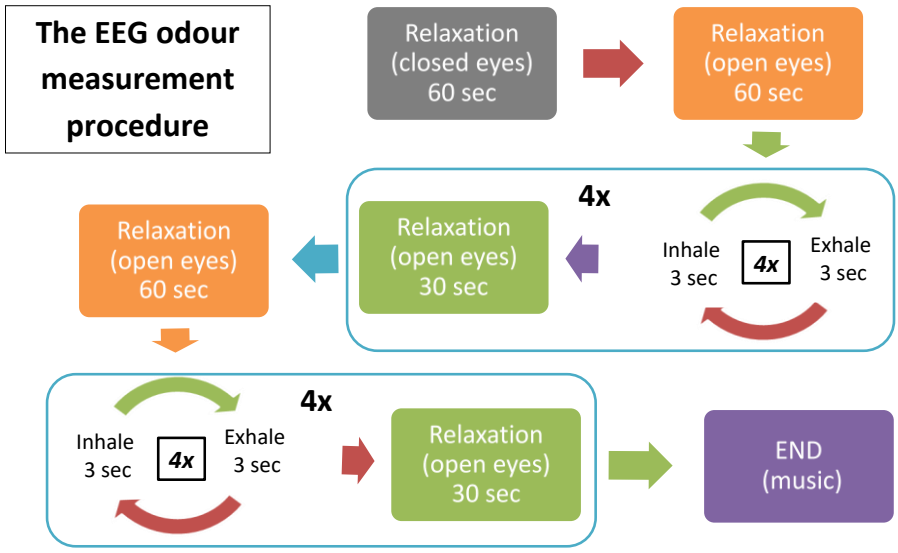
Samples were homogenized and filtered through Whatman MN-615 filter paper prior to analysis. EBC values were determined according to the standard Analytica-EBC color measuring method. The absorbance was determined in 1 cm UV VIS cuvettes at 430 nm by a Hach Lange DR6000 UV-VIS spectrophotometer in triplicates. The absorbances then were multiplied by 25. Transmission spectra was determined by a Hach Lange DR6000 UV-VIS spectrophotometer

through the whole visible spectra from 380 to 780 nm with 10 nm steps. Tristimulus values and chromaticity coordinates of the samples were calculated from transmission spectra as defined in the CIE 1931 standard colorimetric system.

2.6 **Sour cherry fragrance and EEG**

In this study, I investigated how brain activity changes in response to a food odor (sour cherry) and whether these changes are related to the subject's current physical and mental state (fatigue, mood, volatility). The research was performed with an Emotiv EPOC+ EEG device. The applied odorant was a food flavoring (sour cherry flavor, Dawn Foods Hungary Kft). The testing protocol and the control software were programmed in Python-based PyCharm. The EEGLAB toolbox software package of MATLAB (MathWorks Inc, 3 Apple Hill Drive Natick, MA 01760-2098, USA) was used for complex evaluation of the results. Fatigue was assessed using the Multidimensional Fatigue Symptom Inventory-Short Form (MFSI-SF), mood using the Positive Affect Negative Affect Scale (PANAS), and odor sensitivity using the Odor Awareness Scale (OAS). The experiments were conducted following the guidelines of the Helsinki Declaration.

In the experiment, a time frame of 3 seconds was set for inhaling the fragrance and 3 seconds for exhaling it. The time frames were enforced by an automatic beep that sounded at the start of inhalation and exhalation. During the test, one block lasted 24 seconds and consisted of 4 odorizations (4x3 sec of odorization and 4x3 sec of exhalation). The blocks were separated by 30 seconds of relaxation to allow the nose and olfactory receptors to regenerate. The total experiment consisted of 8 blocks, half of which (after block 4) included a longer (60 s) relaxation break. The end of the trial was signaled by music. The flow diagram of the measurement is shown in Figure 3.



3. Figure: Flowchart of the odor measurement

2.7 Psychometric functions of difference tests

The psychometric function gives the functional relationship between the sensory distance (δ) of the products and the proportion of distinguishers (P_d). In all cases the relationship is method specific. The results of the comparative study can be used to determine the sensitivity of each differentiation test method, i.e. how a unit change in the proportion of distinguishers changes its value, and conversely, how a unit change in P_d affects its value. By characterising the curves, it is possible to subdivide the typical run-off phases and to determine the sensitivity of the difference analysis methods.

In my research, the P_d values were calculated for six difference test methods (2-AFC, duo-trio, 3-AFC, triangle test, tetrad test, two out of five tests) using the XL-Stat program.

2.8 Különbségvizsgálatok multikritériumos értékelése

In practice, the comparison of difference tests can be based on a number of parameters, but no system has yet been published that can handle the effects of changing several input parameters simultaneously. A suitable tool for this purpose could be the Sum of Ranking Differences (SRD) method, which is a simple, fast and general technique for comparing different individuals, methods or models.

In developing this method, I have compared different simulated experiments:

Research question 1 (theoretical): Can completely different difference tests be compared? *Realization*: A theoretical comparison of experimental set-ups: comparison of several difference test methods by varying the possible parameters for different products.

Research situation 2 (practical): Decision must be made in a sensory laboratory which difference test method to choose for a given number of assessors and food samples? *Realization*: Practical comparison of experimental set-ups: comparison of several methods of difference testing for a given number of grading units, a given material cost and a given sensory fatigue (sample) constant parameters.

3. RESULTS

3.1 Syrups

3.1.1 Results of instrumental color measurements

The color differences between each member of the 10-member dilution series were calculated. Five samples were selected, among which the color differences were close to the theoretical ΔE^*_{ab} = 2 (Table 2). For the red, blue and yellow syrups, the number of dilutions selected was the same (Sample 1: 1:13, Sample 2: 1:11, Sample 3: 1:9, Sample 4: 1:7, Sample 5: 1:5 dilutions), but only one adjustment was required for the green syrup (Sample 2: 1:10).

2. Table: Magnitude of ΔE^*_{ab} differences between different syrup samples

ΔE^*_{ab}	Color of syrups			
Samples	Red	Green	Blue	Yellow
1 ↔ 2	**2.05**	**2.19**	**1.95**	**2.04**
2 ↔ 3	**1.87**	**2.17**	**2.19**	**1.96**
3 ↔ 4	**1.94**	**2.02**	**2.16**	**2.27**
4 ↔ 5	**2.08**	**2.2**	**2.15**	**2.19**

3.1.2 Results of sensory tests

Under artificial daylight (D65), all assessors ranked all the samples in the correct order, with results differing only in the time of ranking. This is the standard lighting environment. Results under colored lighting environments are shown in Table 3.

Results of the Cabilio-Peng pairwise comparison:

- Sample 3 and 4 of the red syrup series did not differ significantly under red illumination.
- Sample 1 and 2 of the green syrup series did not differ significantly under Light 3 (G80+B10+A10).
- Sample 1, 2 and 3 of the blue syrup series did not differ significantly under blue illumination.
- Sample 1 and 2 and 2 and 3 of the blue syrup series did not differ significantly under Light 3 (B100+R100).
- Sample 1 and 2 of the blue syrup series did not differ significantly under Light 4 (B100+G100).
- Yellow syrup series 1 and 2 did not differ significantly under any of the illuminations tested.
- Sample 3 and 4 of the yellow syrup series did not differ significantly under Light 3 (B100).

3. Table: The correct ranking broken down by number for each syrup under different coloured light conditions (B: blue, R: red, G: green, A: amber, the number after that shows the percentage of the LED actual working capacity)

		1st place	**2nd place**	**3th place**	**4 th place**	**5 th place**	**Time avg (s)**	**Time st. dev. (s)**
Red syrup	**D65**	**100%**	**100%**	**100%**	**100%**	**100%**	**17.8**	**2.9**
	B100	100%	100%	100%	100%	100%	14.1	2.4
	R100	100%	71.4%	64.3%	71.4%	100%	25.2	4.2
	B100+R100	100%	100%	100%	85.7%	85.7%	13.4	2.1
	R80+G10+B10	100%	85.7%	85.7%	100%	100%	17.2	3.3
Green syrup	**D65**	**100%**	**100%**	**100%**	**100%**	**100%**	**17.4**	**5.8**
	B100	100%	100%	100%	100%	100%	20.4	7.1
	R100	100%	100%	100%	100%	100%	20.1	7.0
	G80+B10+A10	57.1%	57.1%	71.4%	85.7%	100%	27.4	8.2
	R50+G80+B10	100%	100%	100%	100%	100%	20.0	4.5
Blue syrup	**D65**	**100%**	**100%**	**100%**	**100%**	**100%**	**19.1**	**6.7**
	B100	21.4%	28.6%	50%	100%	100%	19.3	4.6
	R100	85.7%	71.4%	92.9%	92.9%	100%	21.2	3.6
	B100+R100	64.3%	42.9%	57.1%	78.6%	85.7%	21.0	3.7
	B100+G100	71.4%	71.4%	100%	100%	100%	13.4	3.0
Yellow syrup	**D65**	**100%**	**100%**	**100%**	**100%**	**100%**	**16.9**	**6.5**
	B100	42.9%	42.9%	85.7%	100%	100%	24.0	8.4
	R100	64.3%	64.3%	85.7%	78.6%	85.7%	24.4	8.6
	A100	71.4%	71.4%	71.4%	57.1%	71.4%	24.1	10.8
	A50+G50	71.4%	71.4%	78.6%	78.6%	100%	24.1	9.9

Based on Kaplan-Meier survival analyses, the following can be summarized: for the Red syrups, red light had a relevant masking effect, while the other two illumination (100% blue and 100% red +100% blue) had a highlighting effect. For the Green syrups, we found one illumination with masking effect (100% green + 10% blue). For the Blue syrups, evidence of a masking effect in two cases were proven (100% blue and 100% red + 100% blue), of which the 100% blue was more effective, and a highlighting effect was obtained with one illumination (100% blue + 100% green). For the Yellow dilutions, all four illuminations (100% Blue, 100% Red, 100% Amber, 50% Green + 50% Amber) had significant masking effects, but the best efficiency was obtained under Light 3 (100% amber + 10% blue).

4. Table: Summary of Kaplan-Meier survival analyses (B: blue, R: red, G: green, A: amber, the number after that shows the percentage of the LED actual working capacity)

Illuminations (%)		Pairwise comparison (p-value)			Differs from D65?	Direction of difference
		Log-rank	Wilcoxon	Tarone-Ware		
Red syrup	B100	*0.0002*	*0.0003*	*0.0002*	Yes	Highlighting
	R100	*<0.0001*	*<0.0001*	*<0.0001*	Yes	Masking
	B100+R100	*0.0002*	*0.0002*	*0.0002*	Yes	Highlighting
	R80+G10+B10	0.9869	0.6698	0.7901	No	-
Green syrup	B100	0.9579	0.9088	0.8739	No	-
	R100	0.9874	0.9452	0.9137	No	-
	G80+B10+A10	*<0.0001*	*0.0005*	*0.0001*	Yes	Masking
	R50+G80+B10	0.9311	0.9817	0.8918	No	-
Blue syrup	B100	*0.0102*	*0.0064*	*0.0072*	Yes	Masking
	R100	0.1587	0.0529	0.0835	No	-
	B100+R100	*0.0264*	*0.0068*	*0.011*	Yes	Masking
	B100+G100	*0.0405*	0.0631	*0.0489*	Yes	Highlighting
Yellow syrup	B100	*0.0008*	*0.0017*	*0.0012*	Yes	Masking
	R100	*0.001*	*0.0009*	*0.0008*	Yes	Masking
	A100	*0.001*	*0.0037*	*0.002*	Yes	Masking
	A50+G50	*0.0006*	*0.0012*	*0.0008*	Yes	Masking

In summary, the results show that some light environments have a masking effect and some light environments have a highlighting effect, depending on the color of the product and the color range of the lighting.

3.2 Chocolates

3.2.1 Results of instrumental color measurements of chocolates

The results of the instrumental measurements proved that there is a linear variation between the colors of the chocolates (R^2_{L*}= 0.948 R^2_{a*}= 0.979; R^2_{b*}= 0.972). Based on the ΔE^*_{ab} values, the number of samples in the selected series and their cocoa content are: 1st (3.00%) - 3rd (4.50%) - 4th (5.25%) - 6th (6.75%) - 9th (9.00%). The ΔE^*_{ab} color differences between them are 2.75 ↔ 2.59 ↔ 2.42 ↔ 2.39.

3.2.2 Results of sensory tests (Experiment 1)

In Experiment 1, we investigated whether there is a significant difference in masking power between monochromatic lights. Descriptive statistics show that under the reference illumination (D65, white), all assessors ranked the chocolate samples correctly and in the shortest time. The most errors were made under the Blue illumination, and this lighting condition was the one that prolonged the ranking time the most, which more than doubled compared to D65 (15.74 s →35.7 s). This suggests that the monochromatic Blue light environment was the most efficient of all the

color environments tested. After Blue, Green and Amber illumination proved to be effective masking lights (Table 5).

5. Table: Results of Experiment 1: Sensory effects of monochromatic illumination of chocolate samples (descriptive statistics)

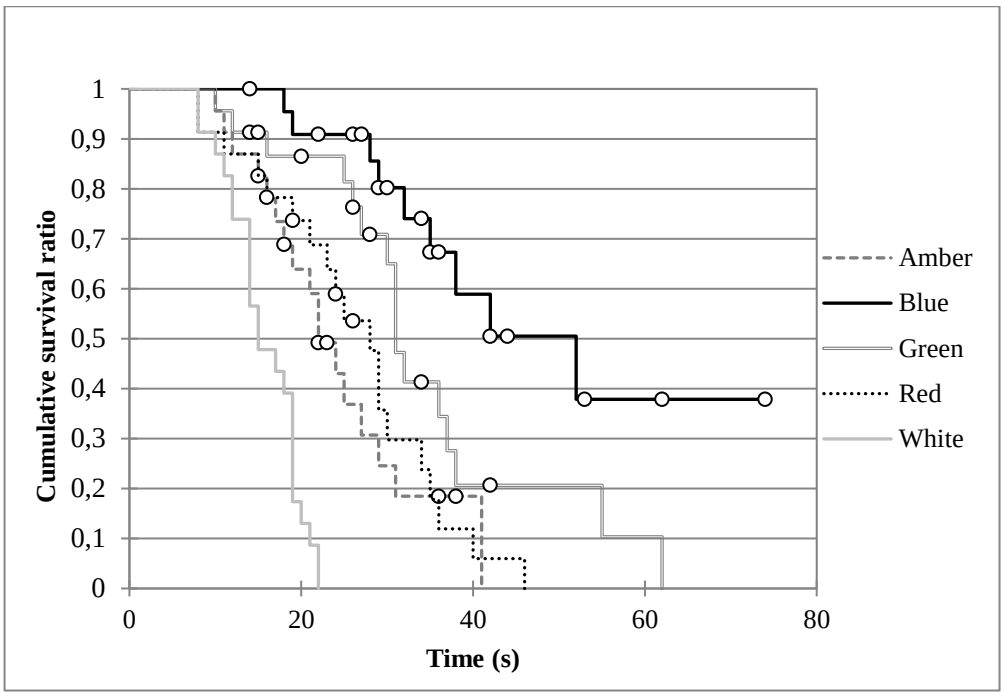
Color of illumination	**D65**	**Red**	**Green**	**Blue**	**Amber**
Correctly ranked (pcs)	23	19	16	9	17
Incorrectly ranked (pcs)	0	4	7	14	6
Avg. time of ranking (s)	15.74	24.43	29.48	35.70	22.26
St. deviation of ranking (s)	4.27	9.90	12.67	14.30	8.38
Avg. time of scaled ranking (s)	*0.448*	*0.649*	*0.785*	*0.945*	*0.622*
St. deviation of scaled ranking (s)	*0.138*	*0.162*	*0.197*	*0.115*	*0.217*

By examining the assessors' ranking times, we sought to determine whether there was a significant difference between the rankings under each illumination. Evaluation of both the real-time data and the scaled data showed that the ranking under Blue illumination was found to be significantly the longest compared to all other illuminations, while the landing under White illumination was found to be the shortest compared to all other illuminations. Significant order of ranking time of scaled data (shortest to longest): white→ amber, red→ green→ blue.

6. Table: Results for ranking, real and scaled time based on significant differences by Duncan's post hoc test (Experiment 1)

Real time data					Scaled time data				
Illumination	*Mean (s)*	*Groups*			*Mena (s)*	*Groups*			
Blue	35.69	A			0.94	A			
Green	29.47		B		0.78		B		
Red	24.43		B	C	0.64			C	
Amber	22.26			C	0.62			C	
White	15.73				0.44				D

Effectiveness of masking illuminations based on survival analysis (from most to least effective): blue → green → red, amber. To summarize the results, each of the tinted light environments tested has a masking effect compared to white (D65) light, but their effectiveness varies.



4. Figure: Survival functions based on Kaplan-Meier analysis

3.2.3 **Results of sensory tests (Experiment 2)**

In Experiment 2, we investigated whether the spectral content of masking illumination could be extended to provide better chromatic adaptation conditions (with minimal sensory fatigue in the visual system) while maintaining masking efficiency. Based on the results of Experiment 1, the design of Experiment 2 was established. Since Blue light gave the best masking efficiency in that experiment, its brightness was kept at the maximum in all cases in Experiment 2. In order to extend the spectral content, we tested three to three additional settings of Green (G33, G67, G100) and Amber (A33, A67, A100) with different brightness levels (33%, 67%, and 100%).

The descriptive statistics of the results showed that of the combined lights, the G33+B100 lighting environment had the greatest effect on the alignment of the chocolates. Ranking time increased most with the G67+B100 setting. Based on the correctness of the ranking and the ranking times, A67+B100 and A100+B100 were the two light combinations with the least masking effect.

The results of the sequence analysis showed that more correct responses were obtained under the amber (A67+B100 and A100+B100) mixed illuminations than under the pure Blue (B100), and therefore their masking effect was found to be weaker. However, the combined green (G33+B100, G67+B100 and G100+B100) and low amber (A33+B100) light conditions did not differ significantly from the pure Blue (B100) results. For optimization, the Smet adaptation factor was calculated to account for chromatic adaptation. Considering the maximum adaptation and maximum masking effect, the recommended masking environment is A33+B100.

7. Table: The results of the post hoc Duncan's test for significant differences in the correctness of the ranking (Experiment 2) and the degree of adaptation (in case of Illumination: B: blue, R: red, G: green, A: amber, the number after that shows the percentage of the LED actual working capacity)

Illumination	Mean (s)	Groups		Degree of adaptation
A100+B100	0.8696	A		1.9987E-01
A67+B100	0.8696	A		8.9775E-02
G100+B100	0.6087	A	B	5.4490E-02
G67+B100	0.5217		B	1.2583E-04
A33+B100	**0.4783**		**B**	**4.0501E-02**
G33+B100	0.4348		B	1.2757E-05
Kék (B100)	0.3913		B	1.7613E-07

The results of the ranking time test show that G67+B100 and G33+B100 illuminations had similar efficiencies to pure Blue (B100) light. The results confirm that, among the masking light environments that do not differ significantly from Blue light in terms of masking efficiency, the A33+B100 combination gave the shortest real (25.13 s) and scaled (0.62) times for the sorting of chocolates. It can be seen that the scaled data allow to identify more distinct groups.

8. Table: Results for ranking, real and scaled time based on significant differences by Duncan's post hoc test (Experiment 2) (in case of Illumination: B: blue, R: red, G: green, A: amber, the number after that shows the percentage of the LED actual working capacity)

Real time data						Scaled time data					
Illumination (%)	*Mean (s)*	*Groups*				*Illumination* (%)	*Mean*	*Groups*			
Blue (B100)	35.69	A				Blue (B100)	0.83	A			
G67+B100*	34.91	A				G67+B100*	0.79	A			
G33+B100*	32.21	A	B			G33+B100*	0.77	A	B		
G100+B100*	28.39	A	B	C		G100+B100*	0.66		B	C	
A33+B100*	25.13		B	C	D	A33+B100*	0.62			C	
A67+B100	23.91			C	D	A67+B100	0.57			C	D
A100+B100	20.34				D	A100+B100	0.48				D

**light combinations under which the masking effect was not significantly different ($p<0.05$) from the Blue (B100) illumination efficiency*

Based on the survival analysis, the best masking lights are pure Blue (B100), G33+B100 and G67+B100. It can be concluded that the addition of green light did not improve the masking effect of Blue (B100), but worsened it for G100+B100. The Kaplan-Meier test statistic results showed that A67+B100 and A100+B100 illuminations differed from all other illuminations except each other. In summary, the combination of lights failed to produce a masking light environment more effective than the monochrome Blue (B100) illumination.

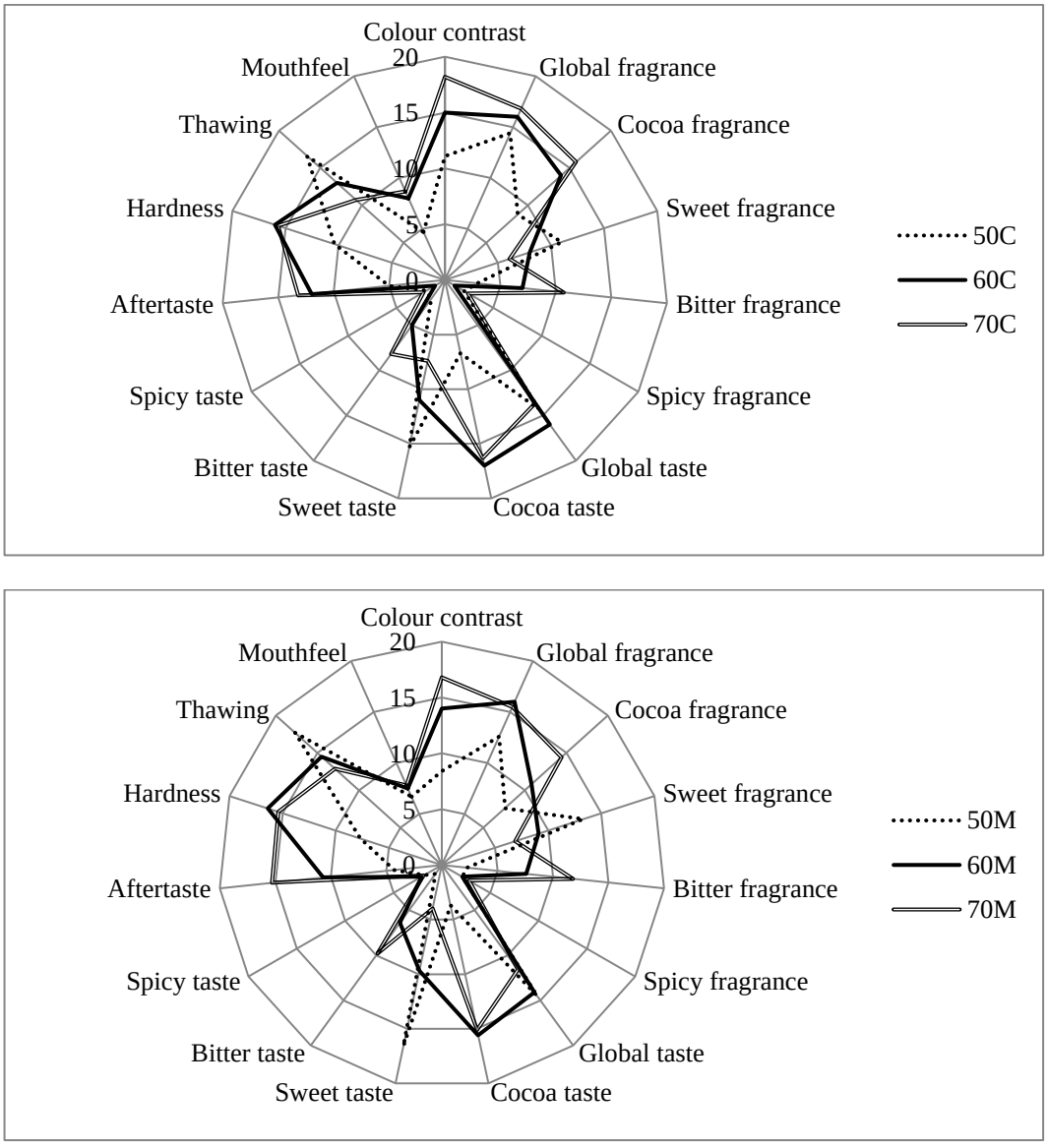
3.3 Cross modality (chocolates)

3.3.1 Visual tetrad test

Based on the difference-in-difference test performed by 32 assessors, we found (α=5%) that there was no visual difference between only two of the six chocolate samples (70C and 70M). In all three cases the samples with the same cocoa content were lighter than those with maltitol, and that the darker the samples (higher cocoa content), the more the color differences due to sweeteners were reduced.

3.3.2 Sensory test result (by tasting) under reference light (D65)

The research question was whether different color ranges could be used to influence other characteristics of chocolates (aroma, flavor, texture) in addition to visual parameters. The results of the tests under colored light conditions were compared with those obtained under artificial sunlight (D65). The 60C sample was chosen as reference.



5. Figure: Sensory profile of products containing sugar (top) and maltitol (bottom)

General patterns can be observed for both sugary and maltitol samples. The color contrast data show that the more cocoa powder a chocolate contains, the darker the color. Global fragrance, cocoa fragrance and bitter fragrance follow the proportion of cocoa powder. The sweet fragrance results show the opposite pattern to the cocoa fragrance, as the more cocoa powder the samples contained, the less sugar. Flavor notes also correspond to expectations, as they follow the trend of more cocoa powder: higher cocoa/tart flavor, while sweet flavor follows the opposite trend. In terms of aftertaste and hardness, the 50% samples fall short of the higher cocoa content samples.

3.3.3 Sensory test results under colored lights

The effects of lighting environments were always compared to the test results of the white light (D65) lighting environment per chocolate sample and per sensory attribute (α=1%, one-tailed analysis of variance, Duncan's post hoc test). An idea of the influence of colored lights can be obtained by comparing responses to the same samples under different colored light environments.

9. Table: Effects of light environments at 1% significance level

α =1%	**Green**		**Blue**		**Red**	
	More intense	**Less intense**	**More intense**	**Less intense**	**More intense**	**Less intense**
50M	bitter fragrance (*p*=2.6E-05)		cocoa taste (*p*=0.0059)		cocoa taste (*p*=0.0003)	
			aftertaste (*p*=0.0009)			
50C	bitter fragrance (*p*=0.0006)		aftertaste (*p*=2.7E-05)		cocoa taste (*p*=0.0092)	
	aftertaste (*p*=0.0043)				aftertaste (*p*=0.0023)	
60M			cocoa fragrance (*p*=0.0055)			
70M						
70C		color contrast (*p*=0.0005)				

**No difference was found at the 1% alpha level under amber and orange illumination, so these masking colors are not shown in the columns of the table*

At an α level of 1%, I determined the following.

1) Green, blue and red lights can be used to intensify certain sensory qualities in chocolates containing 50% and 60% cocoa.
2) The green color light resulted a more intense bitter smell for 50M, and a more intense bitter smell and more intense aftertaste for 50C.
3) The blue color light resulted a more intense cocoa flavor and a more intense aftertaste at 50M, a more intense aftertaste at 50C, and a more intense cocoa odor at 60M.
4) The red color light resulted more intense cocoa flavor at 50M, more intense cocoa flavor and aftertaste at 50C.

5) The green, blue and red colours have an effect mainly on chocolates with 50% cocoa content, only the blue colour has an effect on chocolates with 60% cocoa content.
6) Chocolates with 70% cocoa content are not significantly (1%) affected by the colour environment.
7) Amber and orange had no significant (1%) effect on any of the sensory attributes.

3.4 Beer color test results

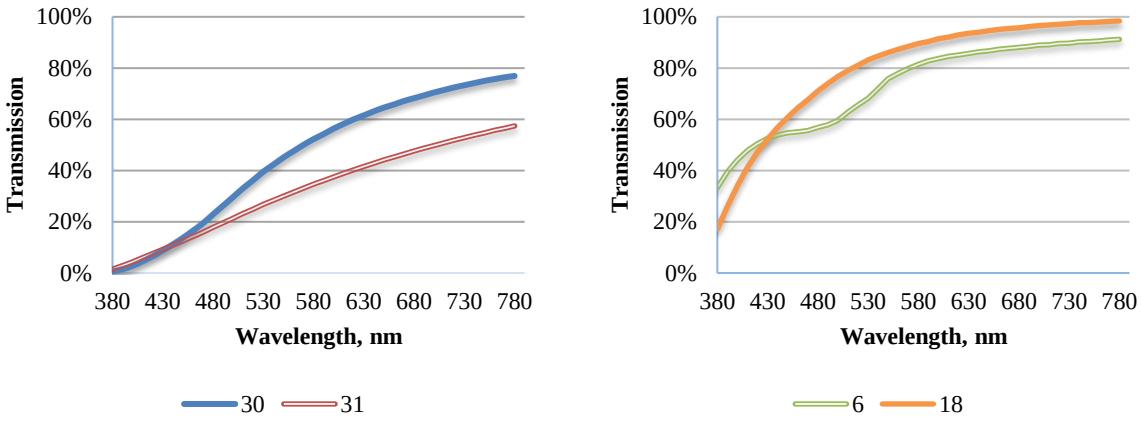
The exact EBC and CIELAB values of the tested beer samples are presented in detail in the PhD thesis.

3.4.1 Differences in color determination methods

1. Table: Differences between European Brewery Convention (EBC) and CIELAB system

Sample nr.	*EBC diff.*	*ΔE*ab diff.*	*Degree of visually perceptible difference (by Zhu et al. [2013])*
Weissbier (30) Weissbier (31)	0,6	17,4	significant difference
Non-alcoholic beer-based drink with lemon juice (5) Belgian strong pale ale (28)	0,3	12,6	significant difference
Non-alcoholic beer-based drink with grapefruit juice (6) European pale lager (18)	0,1	7,7	significant difference
International amber lager (24) Irish red ale (34)	1,6	7,3	significant difference
Irish stout (35) Dunkles bock (36)	1,1	4,5	some difference

The difference between the two tested weissbier (30 and 31) is only 0.6 when measured in the EBC system, but the difference in ΔE^*_{ab} is extremely large (17.4) and the two beers differ greatly in the transmission spectrum (Figure 6). The EBC difference between sample 5 (non-alcoholic beer-based beverage with added lemon juice) and sample 28 (Belgian strong pale ale) is 0.3, while the ΔE^*_{ab} difference is12.6. In contrast, sample 6 (non-alcoholic beer-based beverage with added grapefruit juice) and sample 18 (European pale lager) are identical according to the EBC scheme, but the ΔE^*_{ab} difference according to CIELAB is 7.7, which is due to the difference in the data measured at 420-520 nm (Figure 6). Comparing beer sample 24 (International amber lager) to beer sample 34 (Irish red ale) (EBC=1.6; ΔE^*_{ab} =4.5) and sample 35 (Irish stout) to beer sample 36 (Dunkles bock) (EBC=1.1; ΔE^*_{ab} =7.3) also shows that there is a small difference in the EBC color scheme but a large difference in ΔE^*_{ab}.



1. Figure: Transmission spectra of two-Two beer samples tested

3.5 EEG and cherry fragrance

3.5.1 Comparison of air (A) and cherry (C) scents based on the signal elicited

The first research question was whether the EEG signals elicited by air and cherry smell differ between channels and between people. Accordingly, the EEG signals were analysed by channel (delta, theta, alpha, beta, gamma) after performing the condition tests, using an one-tailed ANOVA (α=0.05).

2. Table: Deviation from the reference for the cherry fragrance (top rows show the direction of deviation, bottom rows the p-values calculated by ANOVA, bolded lines show significant (α=0.05) differences)

	Delta	Theta	Alfa	Beta	Gamma
1	**C↑** ***0,0149***	No *0,1537*	No *0,3719*	No *0,0545*	**C↓** ***0,0214***
2	No *0,154*	**C↓** ***0,046***	**C↓** ***0,024***	No *0,113*	No *0,055*
3	**C↑** ***0,009***	**C↑** ***0,009***	No *0,449*	No *0,814*	No *0,671*
4	**C↑** ***0,016***	**C↓** ***0,044***	**C↓** ***0,036***	**C↓** ***0,025***	No *0,229*
5	No *0,216*	No *0,622*	No *0,108*	**C↑** ***0,007***	**C↑** ***0,0004***
6	No *0,181*	No *0,062*	No *0,546*	No *0,304*	**C↓** ***0,011***
7	**C↑** ***0,002***	No *0,334*	**C↓** ***0,0004***	**C↓** ***<0,0001***	**C↓** ***0,005***
8	**C↑** ***<0,0001***	**C↑** ***<0,0001***	**C↑** ***<0,0001***	**C↑** ***<0,0001***	**C↑** ***<0,0001***
9	No *0,332*	No *0,272*	**C↓** ***<0,0001***	**C↓** ***<0,0001***	**C↓** ***<0,0001***
10	**C↑** ***<0,0001***	**C↑** ***<0,0001***	**C↑** ***<0,0001***	**C↑** ***<0,0001***	**C↑** ***<0,0001***
11	**C↑** ***0,018***	No *0,136*	C↓ ***0,032***	No *0,194*	**C↑** ***<0,0001***
12	No *0,313*	No *0,542*	No *0,130*	**C↓** ***<0,0001***	No *0,087*
13	No *0,102*	No *0,527*	No *0,979*	No *0,457*	No *0,538*
14	No *0,942*	**C↓** ***0,008***	**C↓** ***0,000***	**C↓** ***0,031***	No *0,688*
15	No *0,579*	No *0,062*	**C↓** ***0,015***	**C↓** ***0,042***	No *0,139*
16	**C↑** ***<0,0001***	**C↑** ***0,001***	**C↑** ***0,027***	No *0,088*	**C↑** ***0,031***
17	No *0,081*	No *0,366*	No *0,183*	**C↑** ***<0,0001***	**C↑** ***0,001***
18	No *0,615*	**C↓** ***0,002***	**C↓** ***0,007***	No *0,069*	**C↑** ***<0,0001***
19	**C↑** ***0,048***	No *0,274*	No *0,309*	No *0,700*	No *0,828*
20	**C↑** ***0,001***	No *0,480*	**C↓** ***0,006***	No *0,931*	No *0,081*

The results are inconsistent with this approach, so evaluating EEG signals requires a different approach. It is preferable to consider the first, second, third and fourth inhalations separately, in blocks, rather than the full cycle of 4 inhalations.

3.5.2 Blocked study of the effect of odor

After rearranging the complete cycles of 4 inhalations (by inhalation order) to blocks, the results show that in all cases where there was a significant change between the channel values, the first or second inhalation almost always generated higher values, regardless of the channel. This phenomenon can be explained by the fact that olfactory receptors adapt very quickly to the

stimulus environment. Therefore, significantly weaker EEG signals were obtained in the third and fourth inhalation blocks than in the first and second inhalation blocks.

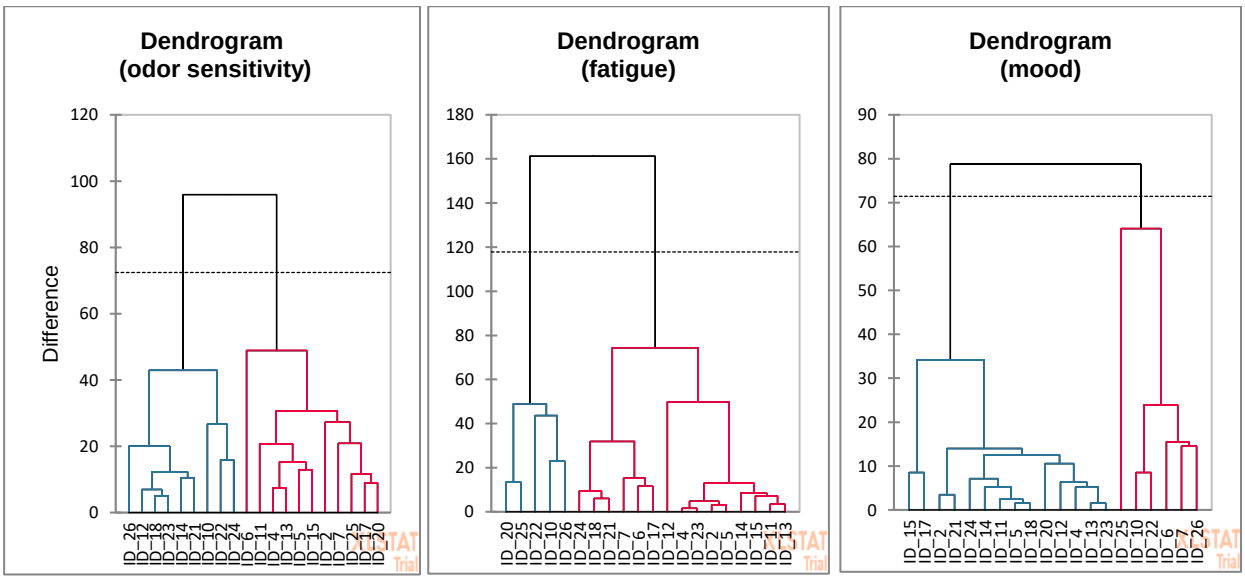
3. Table: Clustering of some delta channel EEG signal sequences according to Duncan's post hoc test, where a significant difference between inhalation blocks was found.

	Block	Mean	Standard error	Lower bound (95%)	Upper bound (95%)	Groups		
10. person	**2.**	0.819	0.054	0.709	0.929	A		
	1.	0.669	0.054	0.559	0.779	A	B	
	3.	0.561	0.054	0.451	0.671		B	
	4.	0.537	0.054	0.427	0.647		B	
11. person	**1.**	0.67	0.045	0.578	0.762	A		
	2.	0.581	0.045	0.489	0.674	A	B	
	4.	0.539	0.045	0.446	0.631	A	B	
	3.	0.528	0.045	0.436	0.621		B	
17. person	**2.**	0.73	0.044	0.64	0.819	A		
	1.	0.572	0.044	0.482	0.661		B	
	3.	0.432	0.044	0.343	0.522			C
	4.	0.333	0.044	0.295	0.474			C

In conclusion, I have created an electroencephalograph (EEG) experimental environment and a test-evaluation system to study the effects of food flavor aroma stimuli.

3.5.3 Comparison of questionnaires and EEG signals

EEG measurements require careful study, as the EEG signals of an individual are influenced by many factors other than the stimuli used as stimuli. Other significant factors may include sensitivity, fatigue and mood factors that vary from individual to individual. Based on the responses to sensitivity, fatigue and mood, 3 different cluster analyses (agglomerative hierarchical clustering, Euclidean distance, Ward's method) were performed, in which the individuals studied were grouped into 2 classes in each case (Figure 7).



2. Figure: Clusters based on odor sensitivity, fatigue and mood

On the basis of the results, two or two distinct clusters were obtained for each of the three criteria (odor sensitivity, fatigue, and mood) as follows:

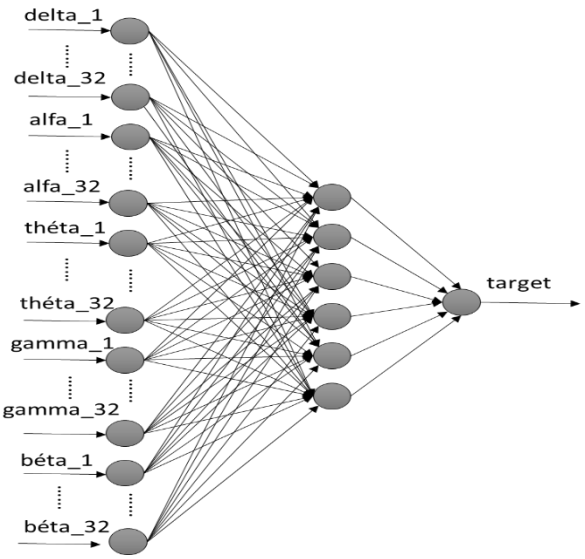
- odor-sensitive (9 participants) and less-sensitive (11 participants) groups of participants were separated in terms of odor sensitivity,
- groups of tired (5 participants) and rested (15 participants) were separated according to fatigue,
- in terms of mood, we separated groups of active (14 participants) and passive (6 participants) participants.

Next, we examined the EEG responses of participants in each cluster to understand the influences of odor sensitivity, fatigue and mood. The recorded EEG signals were standardized for comparability, i.e. each brain signal was correlated to the individual person, making the data for each person comparable. The EEG signals to the cherry stimulus were analyzed by channel (delta, theta, alpha, beta, gamma) using one-point analysis of variance (α=0.05). The results are summarized as follows:

- From the analysis between the clusters separated by odor sensitivity, it was found that the members of the "odor sensitive" group had significantly higher theta, beta and gamma signals.
- The effect of fatigue on EEG signals was significantly higher in the "fatigued" group.
- Regarding the influence of mood, significantly higher values were recorded for delta, beta and gamma channels than for the "passive" group.

3.5.4 **Artificial Neural networks**

A classifier network was built to test the success of a person's EEG signals in determining whether they were produced by the reference (air) or the cherry smell stimulus. The data sets recorded per person were replicated in 100-fold fuzzy simulations (four times, standard deviations ±2.5%, ±5%, ±10% ±20%). Thus, each generated data had a relative deviation from the original (measured) data of at most the chosen standard deviation, and as a consequence the network learned the patterns between the data. Multilayer Feed Forward Networks (MLFN) with 2-6 nodes were constructed and tested (Figure 8). The results showed that the neural networks we built were able to efficiently classify the test data as well. It can be observed that the classification accuracy decreases as the variance increases (Table 13). Nevertheless, even the best neural network (6 nodes) built from a ±20% data set achieved a classification accuracy of more than 95%, which is very good. We can conclude that the pattern in the data is clear even for data with higher noise loadings, the classification was found to be very good.



3. Figure: Schematic picture of the built neural network

4. Table: Results of neural networks with different number of nodes built from simulated data with different variance

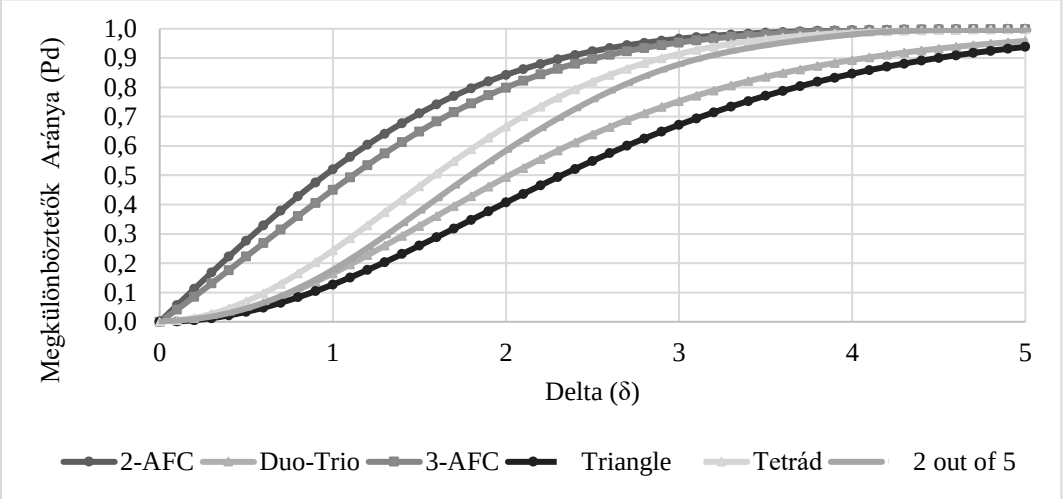
Best Net Search				
	±2.5%	**±5%**	**±10%**	**±20%**
MLFN 2 nodes	2.38%	2.88%	2.38%	5.88%
MLFN 3 nodes	5.00%	0.38%	3.00%	12.00%
MLFN 4 nodes	5.50%	0.63%	2.38%	11.00%
MLFN 5 nodes	**0.13%**	2.00%	3.25%	5.75%
MLFN 6 nodes	**0.13%**	**0.25%**	**2.13%**	**4.75%**

The relative effects of the variables of the constructed neural networks were as follows: ±2.5%: 0.01 - 1.58; ±5%: 0.17 - 1.83; ±10%: 0.04 - 3.2; ±20%: 0.06 - 1.67. That is, I did not find

any variables that really played a prominent role. The 10 variables with the highest values in the constructed feedforward neural networks do not include beta channel signals.

3.1 Psychometric functions of difference testing methods

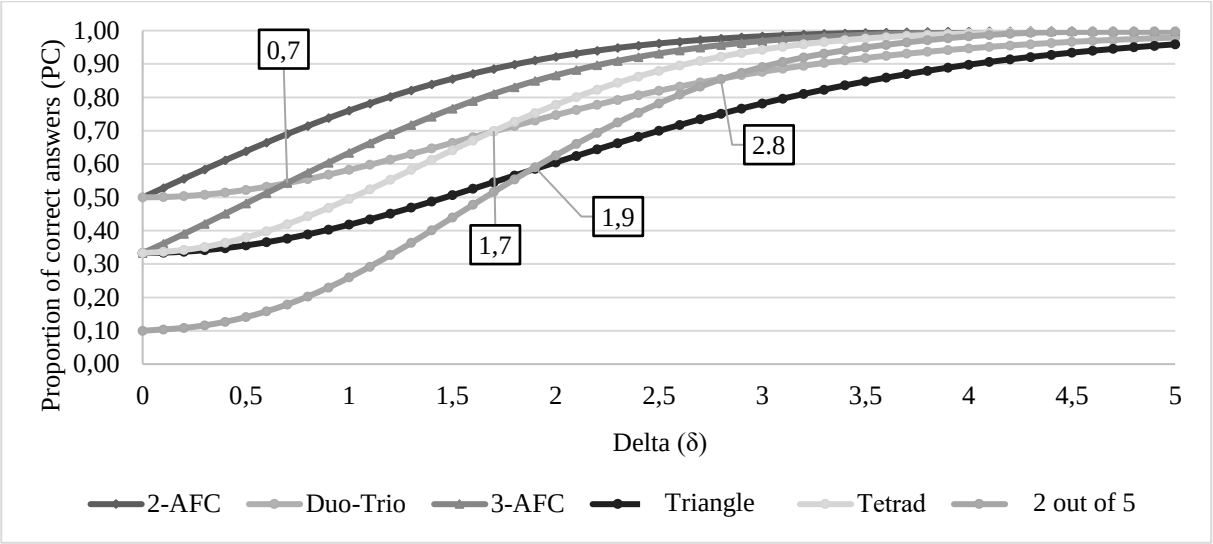
Psychometric functions are curves that represent the relationship between the sensory distance (δ) of products and the proportion of discriminators (P_d) (Figure 9). The plotted data were calculated based on the results of Ennis & Jesionka (2011) and using the Excel macro-based statistical-sensory software V-power.



4. Figure: Psychometric functions of difference testing methods

With respect to the psychometric dependence of each difference testing method, it can be concluded that the proportion of discriminators increases with the increase of the sensory difference between products. The steeper the slope of a curve on the graph, the more sensitive the particular sensory method is to changes in the difference between products. The psychometric functions show a characteristic pattern of the relations of Pd values for a given δ value. Starting from the highest Pd value, the methods take the following descending order of sensitivity: 2-AFC, 3-AFC, Tetrad, Two of Five, Duo-Trio, Triangle.

Knowing the proportion of discriminators, the proportion of correct answers (Pc) can be calculated. From this, a method-specific relationship between the degree of sensory difference (δ) of the products and the proportion of correct answers can be determined (Figure 10).



5. Figure: Connection between the proportion of correct answers and the sensory distances of products for some methods of difference analysis

The intersection between the curves means that at that point, the two difference test methods have the same δ value and the same correct response rate. The number of correct responses to the methods is a function of the sensory distance between the products, so the research question can only be answered if we know the δ-level at which the sensory analysis is performed. These points and the corresponding δ value are marked on the diagram:

- If $\delta<0.7$, the expected proportion of correct responses for the 3-AFC test is lower than for the duo-trio test, but for higher δ, the Pc of the 3-AFC test will be higher.
- If $\delta<1.7$, the expected proportion of correct answers for the tetrad test is lower than for the duo-trio test, but for a higher δ, the Pc of the tetrad test will be higher.
- If $\delta<1.9$, the expected proportion of correct answers for the Two out of Five test is less than that for the Triangle test, but for a higher δ, the Pc of the Two out of Five test will be higher.
- If $\delta<1.7$, the expected proportion of correct answers for the two out of five test is lower than the duo-trio test, but for a higher δ, the Pc of the two out of five test will be higher.

The plotted curves can be classified into two types: saturation functions with no inflection point (2-AFC, 3-AFC), and logistic trend functions with one inflection point (tetrad, two out of five, duo-trio test, triangle test). A characteristic of saturation functions is that as the independent variable increases, the increase in the dependent variable decreases steadily. Logistic trend functions with one inflection point also show monotonic growth, but can be divided into three distinct phases (upswing phase, inflection point, saturation phase), with growth following different trends.

Knowing the shape of the curves and the calculated values, we can fit a function to the curves. The parametric equation describing the saturation curves:

$$y = p_1 + p_2(1 - e^{-p_3 x})$$

Where p1, p2 and p3 are the fitting parameters used to define the regression. The non-linear regression used determines the exact values of the parameters in each case by a series of iteration steps. After performing the calculations, the following formulae were obtained, describing the functional relationship between the proportion of correct responses and the sensory distance between products for the 2-AFC and 3-AFC tests:

2-AFC test: $y = 0.471 + 0.554(1 - e^{-0.791x})$

3AFC test: $y = 0.282 + 0.770(1 - e^{-0.72x})$

Logistic trend function curves can be quantified in a similar way. The general parametric equation describing logistic trend functions:

$$y = p_1 + \frac{p_2}{1 + e^{-p_3(x - p_4)}}$$

The calculations were also performed using non-linear regression with parameter iteration. The functions describing each difference-in-differences test are:

Duo-Trio: $y = 0.423 + \frac{0.564}{1+e^{-1.166\,(x-1.77)}}$

Tetrad test: $y = 0.256 + \frac{0.747}{1+e^{-1.598\,(x-1.472)}}$

Triangle test: $y = 0.243 + \frac{0.743}{1+e^{-1.056\,(x-2.073)}}$

Two out of five: $y = 0.022 + \frac{0.984}{1+e^{-1.579\,(x-1.711)}}$

In each case, the coefficient of determination (R^2) of the logistic models fitted to the data is 1.00, i.e. the models fitted to the points explain 100% of the relationship between delta and the proportion of correct answers.

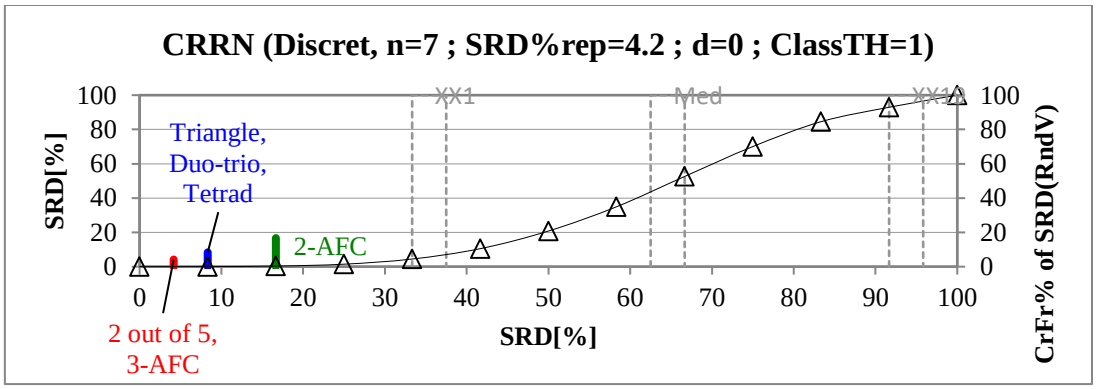
3.2 Multicriteria evaluation of difference testing methods

The SRD method was used to compare the difference-in-differences. In the first (theoretical) research question, we investigated whether it is possible to compare difference testing methods. Based on the runs, we found that the SRD method is suitable for comparing difference analysis methods. The input table of the simulated experiments is shown in Table 14.

5. Table: SRD inputs for the same sample and different test method

	Triangle	Duo-trio	2 out of 5	2-AFC	3-AFC	Tetrad	*Read*
α	0,05	0,01	0,01	0,1	0,05	0,05	*0,01*
β	0,3	0,2	0,4	0,4	0,3	0,2	*0,2*
Pd (prop. of dist.)	0,4	0,4	0,5	0,3	0,4	0,4	*0,5*
n (nr. of assessors)	20	15	25	12	16	22	*12*
Material costs	3	2	2	1	1	4	*1*
Sensory fatigue caused by sample	2	3	1	2	2	1	*1*
Sensory fatigue caused by method	3	3	5	2	3	4	*2*

All 7 input parameters in the table were randomly varied to test the flexibility of the method. The Read column shows the reference values, with the ideal value from each row. These values were determined row by row. After running the rank differences sum method in software, we obtained the results shown in Figure 11 and Table 15.



6. Figure: Order of difference tests for simulated data compared to the rank sum of differences method (theoretical)

The results showed a clear pattern (starting from the best method): two out of five trials, 3AFC→ Triangle trial, duo-trio trial, tetrad trial → 2AFC. This result demonstrates that the SRD method is suitable for comparing difference detection methods.

6. Table: Order of difference tests for simulated data compared to the rank sum of differences method (left: theoretical, right: practical)

Name	SRD	x < SRD > =x	
2 out of 5	1	1.37E-04	3.90E-02
3-AFC	1	1.37E-04	3.90E-02
Traingle	2	3.90E-02	4.08E-02
Duo-trio	2	3.90E-02	4.08E-02
Tetrad	2	3.90E-02	4.08E-02
2-AFC	4	0.24	0.32
XX1	9	4.44	7.26
Q1	13	20.58	29.11
Med	16	44.52	52.48
Q3	19	69.93	77.39
XX19	23	92.87	97.15

Name	SRD	x < SRD > =x	
2-AFC	0	0	1,98E-02
Triangle	2	3.90E-02	4.08E-02
Duo-trio	2	3.90E-02	4.08E-02
3-AFC	2	3.90E-02	4.08E-02
2 out of 5	3	4.08E-02	0.24
Tetrad	3	4.08E-02	0.24
XX1	9	4.44	7.26
Q1	13	20.58	29.11
Med	16	44.52	52.48
Q3	19	69.93	77.39
XX19	23	92.87	97.15

In the other, practical case (given food product, given number of assessors: which test to use), the SRD method is suitable. Among the parameters presented in Table 14, α, β, Pd and the sensory fatigue caused by the method can be varied in this case. The result is shown in Table 15.

It can be seen that for the given cement parameters, the 2-AFC method not only approximates but also matches the theoretical best method. The next group includes the triangle test, the duo-trio test and the 3-AFC test, while the least preferred difference test method for the present data is the two out of five test and the tetrad test.

4. CONCLUSIONS AND PROPOSALS

The conclusions of sensory assessments are based on sensory assessment data, and international (ISO) standards are of paramount importance in the design, implementation and evaluation of sensory assessments. Therefore, standards are the necessary conditions to ensure that sensory tests are reliable, reproducible and comparable. For both consumer and trained and expert assessors, the right sensory assessor is the cornerstone of sensory testing. Trained and expert raters participate in a series of raters' selection tests - taste recognition, taste threshold tests, odor recognition, color recognition, hue, color contrast tests, etc. - followed by a multi-stage iterative performance monitoring system.

If the sensory test is not based on visual assessment, it is recommended to create test conditions in which the assessors are not influenced by visual differences in the assessment. A number of methods have been developed to overcome this - eye-binding, food coloring, tinted

sample dishes, spectrally fixed fluorescent tubes, tinted spectacle lenses - but sensory color masking techniques used in practice have been shown to be error-prone and thus have very limited applicability to a color-specific product.

The standard color comparison requires that assessors have normal vision, perform sensory tests under reproducible lighting and in a reproducible visual inspection environment in the assessment booths of a sensory laboratory. For sensory tests, assessors should not have any deficiency that could affect their perception or adversely affect their sensory performance, which could reduce the reliability of their assessments, and therefore sensory screening tests are required. Human vision, and thus the vision of sensory raters, is fundamentally determined by three factors: visual acuity, contrast sensitivity and color vision. Of these three factors, contrast sensitivity and color vision testing are standard specifications. Color vision testing is primarily aimed at detecting color misleading assessors, typically using pseudo-isochromatic tests. In my practical experience, color misleaders generally have a weaker color discrimination ability and thus perform poorly in Farnsworth-Munsell color discrimination tests, among others.

According to ISO 3389:2007, special lighting devices may also be needed to mask color or visual differences in product color assessment (dimmers, colored light sources, colored filters, black light or monochromatic light sources). As our results have shown, the masking effect of red light, which is most commonly used in sensory research practice, is largely product color specific. In a test with chocolates, we have demonstrated that, in order to ensure a higher degree of chromatic adaptation, enrichment of the spectral content of the most effective masking illumination can be achieved without loss of masking efficiency. In the future, it would be desirable to develop devices that are suitable for creating spectrally controllable environments in sensory laboratories to achieve product color-specific color masking. The practical implementation of this is still difficult for most sensory laboratories today, but the spectrally tunable light booth outlined in my work could be of help to sensory professionals because of its simplicity and wide applicability. Its uptake in sensory laboratory practice is likely.

The results on masking have only been demonstrated for food samples used in experiments (chocolates, syrups), but they contribute significantly to the knowledge available on sensory color masking (adaptation, spectral content, controllability, etc.). The significance of these results is increased by the fact that, to my knowledge, color masking of foods has not yet been performed using a spectrally controllable light booth.

I have done further research on food colors. For beers, I have demonstrated that by using CIELAB color coordinates and derived parameters calculated from transmission spectra recorded every nanometer in the range visible to the human eye (=380-760nm) instead of measuring at a single wavelength (=430nm), beers can be characterized in more detail and with greater

confidence. In the case of fruit beers and beer-based beverages, the single wavelength (=430nm) color measurement method (EBC) is often not able to adequately distinguish between visually different products. These products have a different absorption or transmission spectrum than beers without fruit produced by conventional technology. The different colors can be explained mainly by the different carotenoid, anthocyanin content. It is instructive to note from the results that three of the five pairs of products with less than 5% EBC color difference were conventional beer types. The largest visual difference was for two Weissbier beers with an EBC color difference of less than 5%. The production technology and recipe of these beers are very similar as they are the same beer type. It is therefore particularly important that a single measurement at a single wavelength is not sufficient to accurately describe the color of a product, even if it is a traditional beer type. Given the increasing number of products containing fruit, special base and additives, and the wide variety of commercially available malt types, I propose to review the EBC color determination and develop a new standard method based on the results.

In cross-modal perception (intersensory coordination), information input through the sensory channels (sight, smell, taste, touch, hearing) is brought into contact with each other. Research has now shown a back-and-forth cross-modal effect between each of these sensory modalities. Taking this research further, cross-modality studies have investigated cross-modal concordance (cross-modal association), which describes the fit between different sensations. In cross-modal association, the relationship of a sign, symbol or icon with different modalities was investigated. It may be useful to extend color association research to different cultures, as it has been shown that consumers have different taste and smell expectations for different colors due to their different cultural backgrounds and experiences.

In my work on 50% and 60% cocoa chocolate, I have demonstrated that cross-modality can be used to intensify certain sensory attributes by using green, blue and red lights. At the same time, in a masking experiment with chocolates, I demonstrated that blue light can be used to mask small sensory differences between products. It can therefore be concluded that blue light has good masking properties for the products tested, but it should also be taken into account that it can amplify certain sensory parameters. In future research, it would be useful to test the cross-modal effects (direction and intensity) of other light environments in this product range (milk chocolates with lower cocoa content or white chocolates) and to include other product ranges in the studies. The tests should be carried out in a spectrally controlled light booth, as almost any light environment can be created and the tests are well reproducible.

Sensory difference tests are a useful tool for determining the degree of difference or similarity between two test samples. The methods are summarized in the standard "ISO 6658:2017 *Sensory analysis - Methodology - General Guidance*" and described in more detail in separate international

standards. Numerous studies using these methods have been conducted in the international literature. Despite the fact that the difference analysis method selected and applied can have an impact on the results, publications rarely provide a justification of the relevance of the difference analysis method, relying mostly on the experience of the assessor. In my research, I therefore first identified the parameters (α, β, proportion of discriminators, number of assessors, material cost, sensory fatigue caused by sample, sensory fatigue caused by method) that are suitable for comparing difference testing methods, and then demonstrated that the SRD method is effective in the multivariate selection of difference testing methods. The developed decision support system can be used to compare and rank difference testing methods. My results can be directly integrated into the practice of sensory testing.

Sensory studies of EEG measurements have so far mainly focused on the brain current signals induced by specific odorants. The novel approach of my research focused on the effects of odor sensitivity, fatigue and mood on EEG channels (delta, theta, alpha, beta, and gamma). I demonstrated that these factors were significant under test stimulus and test environment.

Neural networks have been used successfully in various researches so far due to several important properties: 1. very complex non-linear computational tools capable of modeling extremely complex functions, 2. learning (the data structure is automatically learned from the representative data using a training algorithm designed in time), 3. widely applicable (they are based on numerical data), 4. parallel, generalization-ready, high speed and fault-tolerant. ANNs are also more robust and outperform other computational methods in six categories: pattern recognition, clustering, function modelling, prediction, optimization and verification. There are three main applications in the field of food science: exploratory analysis, prediction and classification. The testing environment I have created for EEG studies should be extended in the future with additional food flavor stimuli and testing of specific segments (children, people with partial anosmia, people from different cultures, post COVID patients).

5. NEW SCIENTIFIC RESULTS

1. In my research, I have shown that the use of red masking light, which is commonly used in sensory testing, can only be validated in a product colour-specific way. For different cocoa contents (50%, 60% and 70%) of chocolate, I have demonstrated that the blue (λ_{blue}=460 nm) illumination environment produces more effective masking than the red (λ_{red}=627 nm) illumination environment. Red (λ_{red}=627 nm) for red syrup, bluish green (λ_{blue}=460 nm, λ_{green}=523 nm, blue/green=10/90) for green syrup, and blue (λ_{blue}=460 nm)

for blue syrup, and for yellow syrups, bluish amber (λ_{blue}=460 nm, λ_{amber}=596 nm, blue/amber=10/90) lighting environments proved to be effective masking light environments.

2. In my research, I have demonstrated that blue (λ_{blue}=460 nm) illumination environment for red syrup and bluish green (λ_{blue}=460 nm, λ_{green}=523 nm, blue/green=50/50) illumination environment for blue syrup can be used to highlight perceived colour differences between products.

3. In my research I have demonstrated that green (λ_{green}=523 nm), blue (λ_{blue}=460 nm), and red (λ_{red}=627 nm) light environments can induce different cross-modal effects in chocolates.

    a. The green (λ_{green}=523 nm) color environment resulted in a more intense bitter smell for chocolates sweetened with 50% cocoa maltitol, and a more intense bitter smell, more intense aftertaste and longer lasting mouthfeel for chocolates sweetened with 50% cocoa sucrose.

    b. The blue (λ_{blue}=460 nm) color environment resulted in a more intense cocoa flavor and a more intense aftertaste for chocolates sweetened with 50% cocoa maltitol, a more intense aftertaste for chocolates sweetened with 50% cocoa sucrose, and a more intense cocoa aroma for chocolates sweetened with 60% cocoa maltitol.

    c. The red (λ_{red}=627 nm) color environment resulted in a more intense cocoa flavor for chocolates sweetened with 50% cocoa maltitol and a more intense cocoa flavor and aftertaste for chocolates sweetened with 50% sucrose.

4. My research has shown that the international method for measuring beer color (European Brewery Convention, EBC) can give misleading results. I have developed a new method based on the instrumental measurement of the transmission spectrum in the range visible to the human eye (380-760 nm) at nanometer intervals instead of measuring at a specific wavelength (λ=430 nm) (EBC), and characterized by objective CIELAB color coordinates and derived parameters. This allows a more detailed and reliable characterization of beers with their color parameters.

5. In my research, I have determined method-specific psychometric functions (2-AFC, 3-AFC, Duo-Trio test, Triangle test, Tetrad test, Two out of Five test) describing the correlations between the proportion of correct answers and the sensory distance between products. In my research, I determined the parameters involved in the comparison of difference tests, which I used to demonstrate the feasibility of multicriteria comparison on simulated data.

6. I have created a sound-controlled electroencephalograph (EEG) experimental environment and test-evaluation system to study the effects of food aroma stimuli. In my research, I demonstrated that where there was a significant change in EEG channel (delta, theta, alpha, beta, and gamma) values, there were always higher values in the first or second inhalation EEG signals, regardless of channel.

7. In my research, I have shown that, in addition to the test stimulus and the test environment, other significant factors are individual characteristics of mood, fatigue and mood. Participants can be clustered based on their recorded EEG signals and their responses to questionnaires on volatility, fatigue and mood. The resulting clusters were characterized (agglomerative hierarchical clustering, Euclidean distance, Ward's method). By analyzing the EEG signals of the cluster groups to the cherry scenting stimuli by channel (delta, theta, alpha, beta, gamma), I summarized that:

    a. From the analysis between the clusters separated by olfactory sensitivity, it was found that the members of the "olfactory sensitive" group had significantly higher theta, beta and gamma signals.

    b. The effect of fatigue on EEG signals was significantly higher in the "fatigued" group.

    c. As for the effect of mood, significantly higher values were recorded in the delta, beta and gamma channels than in the "passive" group.

8. I have built, tested and validated artificial neural network models based on channel signals of EEG signals. The 6-node multilayer feedforward neural network (MLFN) models selected based on the lowest testing error correctly classified the olfactory stimuli (error < 5%).

6. PUBLICATIONS RELATED TO THE TOPIC OF THE THESIS

Journal articles with Impact Factor:

Nyitrai, Á. G., Urbin Á., Nagy B. V., Sipos L. (2022) Novel approach in sensory color masking: Effects of colored environments on chocolates with different cocoa content FOOD QUALITY AND PREFERENCE 95, 104363 DOI: 10.1016/j.foodqual.2021.104363 (Q1, **IF: 5,565**)

Sipos L., **Nyitrai Á.G.**, Szabó D., Urbin Á., Nagy B. V. (2021) Former and potential developments in sensory color masking – Review TRENDS IN FOOD SCIENCE & TECHNOLOGY 111, 1–11 DOI: 10.1016/j.tifs.2021.02.050 (**D1** 4/332, **IF: 12,563**)

Koren D., Hegyesné Vecseri B., Kun-Farkas G., Urbin Á., **Nyitrai Á. G.**, Sipos L. (2020) How to objectively determine the color of beer? JOURNAL OF FOOD SCIENCE AND TECHNOLOGY 57(3), 1183-1189. DOI: 0.1007/s13197-020-04237-4 (Q2, **IF: 2,701**)

Peer-reviewed journal (MTA list) publications:

Sipos L., **Nyitrai Á. G.**, Szabó D., Urbin Á., Nagy B. V. (2020) Érzékszervi bírálók látásvizsgálati tesztjei – áttekintés ÉLELMISZERVIZSGÁLATI KÖZLEMÉNYEK, 66(4) pp. 3202-3218

Sipos L, **Nyitrai Á. G.**, Szabó D., Dominek M., Urbin Á., Nagy B. V. (2020) Zöld és fekete tea (Camellia sinensis L.) főzeteire specifikált színelmaszkolási rendszer érzékszervi validálása ÉLELMISZERVIZSGÁLATI KÖZLEMÉNYEK, 66(1) pp. 2830-2855

Nyitrai Á. G., Gere A., Sipos L. (2018) Mesterséges neurális hálózatok élelmiszertudományi alkalmazásai és nemzetközi trendjei ÉLELMISZERVIZSGÁLATI KÖZLEMÉNYEK, 64(3) pp. 2140-2163. ISSN 0422-9576

Conference full paper:

Sipos L., **Nyitrai Á. G.** (2019) Spektrálisan szabályozható érzékszervi maszkoló-rendszer fejlesztése *Ifjú Tehetségek Találkozója, SZIEntific Meeting for Young Researchers* Budapest, 2019. december 9., ISBN: 978-963-269-886-1

Conference proceedings (abstracts):

Sipos L., **Nyitrai Á.G.** (2018) Színmaszkolási rendszerek alkalmazása az érzékszervi vizsgálatokban *MTA, Kertészeti és Élelmiszertudományi Bizottság, Élelmiszertudományi Albizottság workshop* (Budapest)

Nyitrai Á.G., Sipos L. (2019) Neurális válaszok mérése, elemzése és felhasználása az élelmiszerkutatásokban *Hungalimentaria* 2019, ISBN 978-963-89274-4-6 (Budapest)

Sipos L., **Nyitrai Á.G.** (2019) Érzékszervi bírálók színvizsgálatai, termékspecifikus színelmaszkolási rendszerek *Hungalimentaria* 2019, ISBN 978-963-89274-4-6 (Budapest)

Nyitrai Á. G., Sipos L. (2019) Műszeres pszichofizikai vizsgálatok és érzékszervi mérése szinergiája: Elektroenkefalográfia (EEG) integrálása érzékszerv illatvizsgálatokba *MTA, Kertészeti és Élelmiszertudományi Bizottság, Élelmiszertudományi Albizottság workshop* (2019) Budapest

Sipos L., **Nyitrai Á. G.** (2019) Spektrálisan szabályozható fénykabin az érzékszervi vizsgálatokban *MTA, Kertészeti és Élelmiszertudományi Bizottság, Élelmiszertudományi Albizottság workshop* (2019) Budapest

Nyitrai Á. G., Urbin Á., Nagy B. V., Dominek M., Sipos L. (2019) Colormasking of chocolate bars by a spectral tuning sensory booth In: *BioSysFoodEng 2019* Budapest

Madaras K., Boros F., **Nyitrai Á. G.**, Csambalik L., Gere A., Sipos L. (2018) A rangszámkülönbségek összege (Sum of Rank-Differences, SRD) módszerkombináció táplálkozástudományi lehetőségei In: Táplálkozástudományi kutatások VIII. PhD konferencia Program és előadás összefoglalók. Konferencia helye, ideje: Budapest, Magyarország, 2018.01.25 (Magyar Táplálkozástudományi Társaság). Budapest: Magyar Táplálkozástudományi Társaság, 2018. pp. 18. Online

Sipos L., **Nyitrai Á. G.**, Hosszú B., Dominek M., Urbin Á., Nagy B. V. (2019) Színelmaszkolás élelmiszeripari minták vizsgálatában *XI*