THESIS OF DISSERTATION

Preference mapping method development

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1. INTRODUCTION

Sensory attributes of food products are important for assessing quality and they also play major role in consumer decisions. The success of the products can be influenced by developing products which meet the consumers' requirements. Sensory analysis conducted during the product development process gives the opportunity to create products on reasonable prices; hence it enhances the success of the product. (Lawless and Heimann, 2010). Modern product development can only be successful by monitoring the ever changing consumer needs and developing products which meet these requirements.

The Institute of Food Technology gives the definition of sensory analysis as follows: *"A scientific discipline used to evoke, measure, analyze and interpret those responses to products that are perceived by the senses of sight, smell, touch, taste and hearing"*. Due to the rapid improvement of sensory analysis, new methods have been introduced and developed in the past few years. The field of sensometrics was established by the need of statistical analysis of these new methods.

Both sensory analysis and sensometrics are still dynamically improving fields with numerous new challenges and unanswered questions. Concluding the literature, the young scientist finds an incomplete puzzle which has missing pieces on different places. Such fields are the analysis and interpretation of multi-dimensional preference maps created using human sensory and instrumental data, building preference maps using ranking data and/or the analysis of just-about-right (JAR) scales.

Predicting consumers' food choices from eye-tracking data is an unknown field from sensometrics point of view. It has a great potential for product developers, packaging designers, marketing experts and food companies as well. During my PhD, some parts of the global puzzle were completed by establishing and validating methods which are useful in research and industrial practice. Furthermore, their applications are introduced on real world problems in different product development studies.

2. MAIN OBJECTIVES

I aimed to introduce new, improved methodologies to build more detailed preference maps which 1) give more detailed picture of the product space, 2) can be used in the practice to choose from models and 3) integrate eye-tracking methodologies. The aims of the main objectives are the following:

1. **Main aims when creating more detailed preference maps:**
   1.1. Applying different three-way statistical methods to analyze more data matrices in order to build more detailed preference maps.
   1.2. Building preference maps using ranking data of consumer sensory tests.
2. **Main aims to give practical solutions for method comparison and selection:**
   2.1. Introducing a method which gives more detailed results than the generally applied ones to evaluate just-about-right (JAR) scales. Furthermore, introducing a new visualization tool to evaluate results
   2.2. Defining the theoretical and practical rankings of the main JAR evaluation methods.
   2.3. Product optimization based on the impact of the JAR variables on the overall liking in a way which combines the outcomes of multiple JAR evaluation methods.
3. **Main aims to integrate eye-tracking into sensory evaluations:**
   3.1. Introducing a new approach for the analysis of decision times based on eye-tracking parameters
   3.2. Integrating eye-tracking measurements for a better understanding of consumers' decisions when choosing food products. Definition of the most accurate statistical models to predict consumer choices.
   3.3. Developing a more accurate methodology to predict consumer choice than that of based on the last fixation.

3. MATERIALS AND METHODS

I have conducted sensory analysis of several food products to obtain proper data sets which were then analyzed by uni- and multivariate statistical methods. When planning and conducting these evaluations, I followed the good sensory practice. Sample preparation was done according to Kilcast; hence the identical amount of samples was prepared by the same person who always used the same digital scale (Kilcast, 2010). Between the evaluations, panelists used still neutral mineral water as taste neutralizer (Sipos et al., 2012). Samples were coded with 3-digit random numbers and presented in full factorial design (ISO 6658:2005). All the sensory tests were conducted in the standardized environment of the Sensory Laboratory of Corvinus University of Budapest which meets the requirements of ISO 8589:2007.

The trained sensory panel consisted of the experts of the laboratory, all trained in accordance with ISO 8586:2012. To ensure the reliability of the data, all the evaluations were done in duplicates by a panel with at least 10 members. Profile analysis was planned, conducted and evaluated in accordance to the relevant ISO standard (ISO 11035:1994).

Næs suggests at least 60 respondents in consumer studies which was strictly followed in every study (Næs et al., 2010). Just about right and Likert scales were also used in my work. Consumers stated their overall liking on nine point hedonic scales, which had two main endpoints: " I don't like it at all" (1) and " I like it very much" (9). The five-point JAR sales had the following points: "too weak" (1), "weak" (2), "just about right" (3), "strong" (4) and "too strong" (5) (ISO 4121:2003, ASTM MNL-63). Consumers were instructed prior to the evaluations about the use of the different scales.

In my research, the main results are method development; hence the applied statistical analyses and the used sensory data sets will be explained in the results section.

4. RESULTS

4.1 Three-way preference maps

In my dissertation, I evaluated the possible use of *parallel factor analysis* (PARAFAC) and Tucker-3 methods to create three-way preference maps of sweet corn hybrids by integrating the results of a consumer, a trained sensory panel and instrumental measurements. The main emphasis was taken on the similarities and differences of the two models. Eight different sweet corn hybrids were evaluated out of which were three super sweet (GSS8529, Overland and Rebecca), and five normal sweet (Jumbo, Legend, Madonna, Spirit and Turbo) hybrids. The created sweet corn preference maps are unique in the international literature. 60 consumers tasted the samples and the results were analyzed using R-project R 3.0.2 and PTAk package.

The widely applied *multidimensional preference mapping algorithm* (MDPREF) assesses the results along one sensory attribute but not all the consumer results. This makes the interpretation of the results tedious and cumbersome.

PARAFAC and Tucker-3 have the advantage of being three-way methods; hence consumer liking, product attributes and hybrids are plotted in one single map. Biplots of the MDPREF algorithm usually plot the results of the overall liking but the three-way models allow the researcher to evaluate the OAL more detailed. The loadings allow to identify more precisely the primary and secondary drivers of consumers' choice (Figure 1).

Results produced by PARAFAC and Tucker-3 are similar in the case of the first and third factor. The main difference comes from the second factor because the Tucker-3 solution differentiates the taste parameter from the appearance and not from the odor. The difference is caused by the methodological differences since Tucker-3 does not create unique factors and all the possible factor combinations are included into the model. In contrary to this, PARAFAC creates unique factor solutions; hence no rotation is needed (which is essential in two-way MDPREF models).

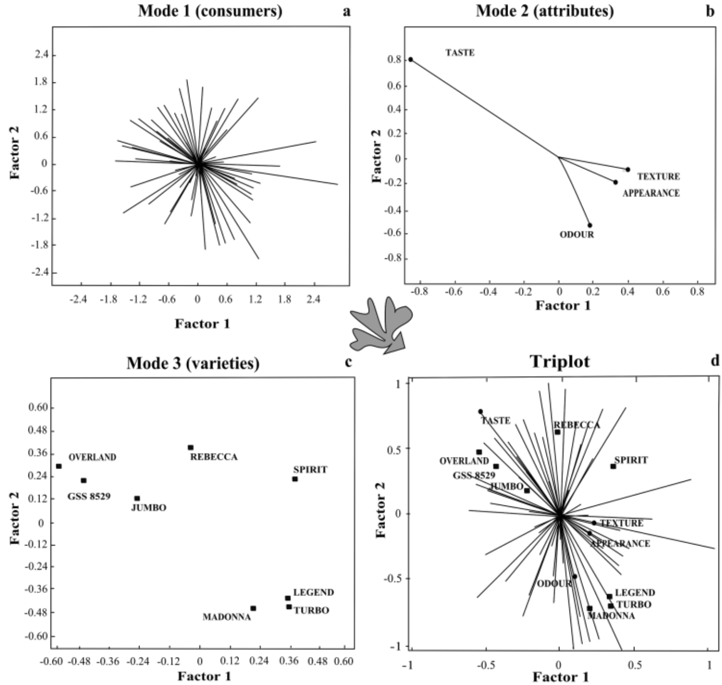

Figure 1: Internal preference map created by PARAFAC (d). The triplot represents the results of all three modes (consumers (a), sensory attributes (b) and hybrids (c)).

I have built three-way preference maps using the data of consumer and trained sensory panel and instrumental measurements. The created maps gave more detailed information compared to the generally applied two-way MDPREF algorithm. Taste was identified as primary driver and odor and texture were the secondary ones for consumers based on the obtained data. My results give more detailed information for sweet corn breeders about the possible ways of development and for the product developers working with sweet corn as raw material.

4.2 Preference maps created from ranking data

Internal preference maps of flavored kefir products have been created based on the answers of 61 consumers. *Categorical principal component analysis* (CATPCA) was applied on the ranking results of the consumer test. In this task, respondents ranked the products according to their overall liking. The two-way CATPCA gave 73.91 % explained variance (Figure 2). Data analysis was done using IBM SPSS Statistics 20 (IBM Corporation, Armonk, USA) software. Figure 2 shows that scores representing the consumers are grouped around currant A and currant B products.

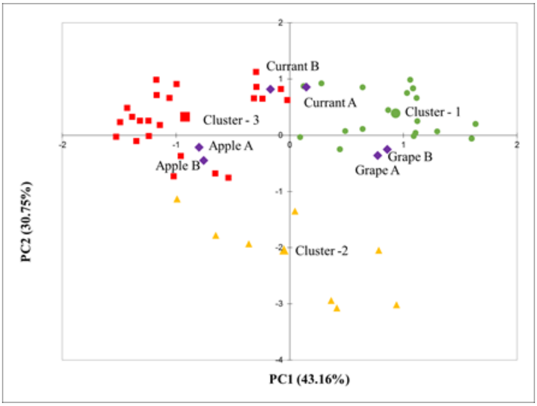

Figure 2: Relationship of the products and the consumers' clusters identified by *k*-means clustering. Green dots (●) represent the members of the first cluster (n=26), the yellow triangles (▲) represent the second cluster (n=9), the red squares (■) represent the third cluster (n=26) and the bigger symbols represent the cluster centroids, diamonds represent the loadings. The higher aroma concentration is indicated by A, the lower is with B.

The proposed method analyzed preference ranks successfully and assessed the stability of the consumers' preference also. MDPREF and CATPCA gave similar results. The advantage of CATPCA is that ranking is an easier task with less bias and mental burden. It requires less time compared to rating. Furthermore, more than six products can be analyzed due to the simplicity of the task. A drawback of ranking is that distances between the samples, expressed on continuous scales, are lost.

4.3 Method development for JAR data analysis

Out of the applied sensory analysis methods, just-about-right (JAR) approaches have been in the focus of the researches in the past few years. Their advantage is that direct information is obtained from the end users about how the product attributes should be modified. In my research, the *generalized pair-correlation method* (GPCM) was applied to analyze JAR data. In GPCM, the input variables (JAR data) are ordered according to their impact on the output variable (overall liking of the product). When dealing with more than two variables, pairwise comparisons need to be done. After a comparison, a variable is considered as "winner", "loser" or "tie" (no decision is made). These outcomes then are ordered in contingency tables which are analyzed by Conditional exact Fisher's test, $\chi 2$-test, McNemar-test and Williams *t*-test.

In my work, 117 consumers tasted flavored mineral water samples. GPCM ranks the JAR product attributes according to their impact on overall liking (OAL). The first attribute should be changed to gain higher product acceptance scores. A new visualization tool was introduced which plots the percentage of consumers along with the rankings of GPCM. This new decision support bubble plot is shown by Figure 3.

The plot is divided into four subspaces using two lines. The horizontal line represents 20 % of the consumers, while the vertical line represents the border of the significant attributes defined by Conditional exact Fisher's test. The size of the bubbles defines the rank of the attributes. The upper left subspace contains the significant and important (> 20 % of consumers' rates) attributes. These attributes should be emphasized during product development. The bottom left subspace contains the significant but not important (< 20 % of consumers' rates) attributes. These have significant effect on OAL for a small number of consumers but not important for the majority. The upper right quadrant shows the non-significant but important attributes. These have little effect on consumer liking but more than 20 % of the consumers rated as true. The bottom right subspace contains the non-significant and not important attributes. The bigger the size of a bubble is, the higher its impact on liking.

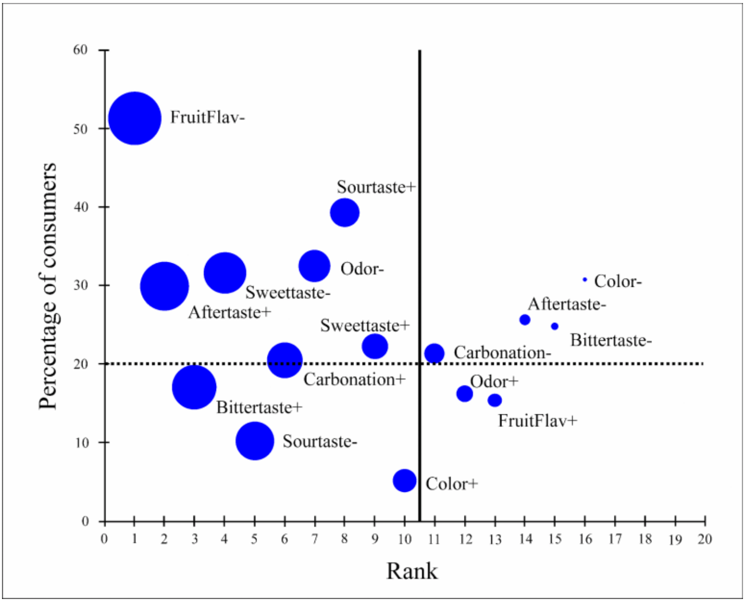

Figure 3. Bubble plot of simple ordering and Conditional Exact Fisher's test. The vertical line divides the significant and non-significant variables. The horizontal line represents 20 % of the consumers. The size of bubbles defines the impact on liking.

The non-parametric GPCM proved to be suitable for analyzing the non-normally distributed data measured on JAR scales. Unlike the methods applied so far, the result is an order, which determines the development of product attributes to gain higher consumer acceptance. Furthermore, GPCM is free to download and run. I found that GPCM can provide differences when other statistical tests cannot and identifies more significant product attributes, so it can help the product development process where other methods cannot.

4.4 Method consensus to optimize product attributes

Numerous methods have been introduced in the literature to analyze JAR data. However, even the standard (ASTM MNL-63) dealing with JAR data analysis and published by the *American Society for Testing and Materials* (ASTM) do not contain any suggestions about which method in which cases should be used. The results of the published methods are in disagreement or contradictory in many cases which makes hard to interpret the results. In my research I supposed that all the JAR methods evaluate the same thing but from different point of view: which variable has the highest impact on OAL? Therefore, if the results of more methods is taken into account, the variables can be defined more precisely. This is a multicriteria optimization problem which can be solved using the *sum of ranking differences* (SRD) method.

SRD has been developed by Héberger (2010) and its validation has been solved by Héberger and Kollár-Hunek in 2011. The SRD method compares the values of an input matrix to a reference variable. The closer a variable to the zero point the more similar it is with the reference column. The cracker data set presented by ASTM MNL-63 was applied to make my results more comparable with standard methods. This contains the evaluations of 117 consumers. Eight different JAR methods were run first then SRD was applied on their outcome.

Further development of the general SRD plot makes it more suitable in product development and JAR data analysis. If the percentages of consumers are plotted on the *y*-axis versus the SRD values, the significant and important (for consumers) product attributes can be identified easily. Figure 4 is divided into two parts along with the solid black line which represents 20 % of the consumers. Attributes which were rated as relevant for the product by the consumers, are located above the line. Changing these attributes results significant increase of overall liking.

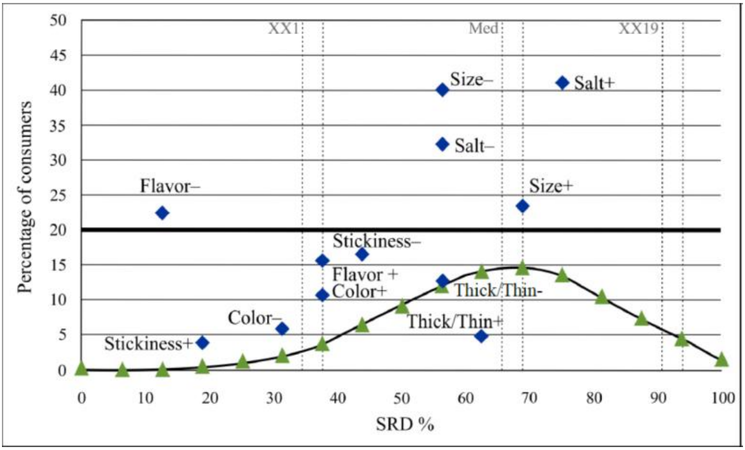

Figure 4. The combination of the results of SRD and the consumers' frequency values. The solid black line represents the 20 % threshold, which is generally applied in penalty analysis as well.

The interpretation of the plot is similar to the SRD plot because the attributes, which have lower values than XX1 can be considered as significant at p = 0.05 level. Therefore, the new visualization tool highlights those attributes which were important for the consumers and those which were identified as significant by SRD. Results show that Flavor– is the most important product attribute and this should be strengthened to achieve better consumer acceptance. Stickiness+ and Color– were mentioned by only a lower percentage of consumers. These consumers disliked the product due to the too sticky and not enough intense color attributes.

The SRD method proved to be a successful tool to rank the JAR variables based on their differences from the reference column (maximum values of the methods) and to prove their significance. The SRD method gives a recommendation for how to optimize the products based on the results of several JAR methods. Further advantages of the method are that the set of the included methods can be easily changed, the results are easy to interpret, there is a freely accessible macro to run and it is user friendly.

4.5 Definition of the best performing method for JAR data analysis

During industrial and product development practice, there is not always sufficient time to analyze JAR data using the method consensus approach in the way I proposed in section 4.4. However, there is a lack of publications dealing with the comparison of the introduced methods. In this part of my research I aimed to answer the question about which JAR method is the closest to the results of the consensus of several methods. In this study, the ASTM MNL-63 data set and SRD method were used, too. A major difference was that the input matrix of SRD was transposed which enabled to compare the methods instead of the attributes.

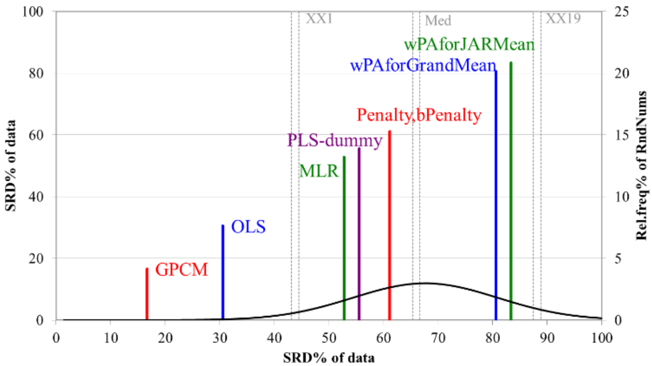

Figure 5. The scaled SRD values of the methods based on the consensus of the methods determined by sum of ranking differences. The row-average was used as reference (benchmark) column. Scaled SRD values are plotted on *x*-axis and left *y*-axis, right *y*-axis shows the relative frequencies (black curve). Probability levels 5 % (XX1), Median (Med), and 95 % (XX19) are also given.

The zero point represents the consensus of the methods because the mean of the rows of the input matrix were in the reference column (Figure 5). Based on the consensus, GPCM proved to be the best. Next to it, the ordinary least squares regression (OLS) is also significantly different from random order. The ranking of the other methods (right from XX1) cannot be distinguished from random ranking. The results showed that the introduced GPCM and OLS should be suggested to evaluate JAR data.

4.6 Analysis of decision times in eye-tracking measurements

Eight product groups were presented for the participants in an eye-tracking study: apple, beer, chocolate, instant soup, salad, sausage and soft drink. They were asked to evaluate four products within each product group. These were arranged in a way to leave the middle of the screen empty. This was necessary because a black fixation cross was presented between the stimuli. This cross standardized the start point of the gaze of all the participants; hence everyone started their evaluations from the same spot.

78 students of the University of Natural Resources and Life Sciences, Vienna (BOKU) participated in the study (aged between 18 and 28 years, 39 males and 39 females) and the results of 59 of them was finally analyzed due to various reasons. Tobii T60 eye-tracker and Tobii Studio (version 3.0.5, Tobii Technology AB, Sweden) software was used to record and analyze the obtained gaze data. The visual stimuli were presented on the screen (17”, 1280 × 1024 resolution) of the static eye-tracker. The study was conducted under controlled (light, temperature) and quiet environment at the Sensory Laboratory of Department of Food Science and Technology of BOKU.

During eye-tracking researches, one-way analysis of variance (ANOVA) is generally applied to compare decision times in most of the published papers. However, eye-tracking data usually does not follow normal distribution and several outliers are present due to the differences of the participants. These all violate the assumptions of ANOVA.

ANOVA evaluates the mean differences. In contrast, survival analysis visualizes, evaluates and compares time variables of both participants and products from the start point until the decision is made. The time between the first mouse click (first contact with the product) to the second mouse click, which shows that the decision is made, was analyzed. Decision curves defined by Kaplan-Meier method give the ratio of those who stated their decision and are plotted in time. Survival analysis was done using Statistica 12.0 (Statsoft Inc. Tulsa, OH, USA).

Figure 6 shows the survival functions of the analyzed products out of which soft drinks have the steepest slope. This means that soft drinks needed the less time to choose one of them. Analysis of the medians of the curves characterizes their first part. This showed that the lowest values were observed for the soft drinks (3.7 s). Median less than 5 s were found at chocolate (4.66 s), sausage (4.79 s) and salad (4.84 s). Participants needed more time to choose apple (5.13 s) and beer (5.16 s). The highest median values were observed when evaluating bread (5.42 s) and instant soup (5.89) product groups. Results showed that participants needed one and a half times more time to choose bread and instant soup than soft drink.

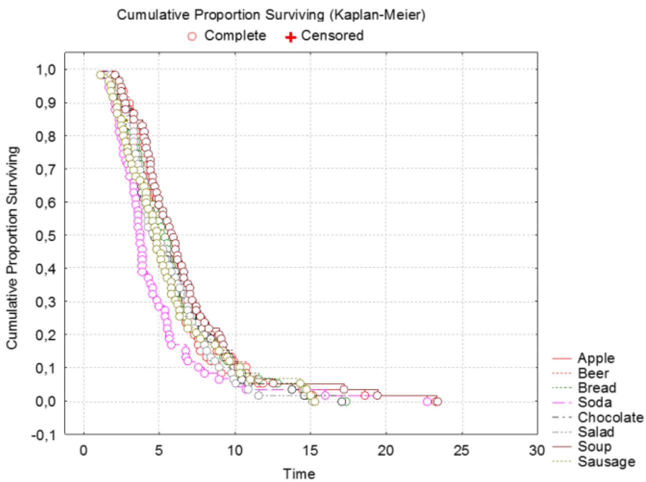

Figure 6. Survival functions created from the data of the respondents (n=59). The curves are defined by Kaplan-Meier method and describe the ratio of those who stated their decision in time.

To analyze the differences, Gehan's generalized Wilcoxon test was run which showed significant differences between soft drinks and almost all the other products. I proved that survival analysis is suitable to compare decision times of different food products. Results showed that participants needed significantly less time to choose soft drink than other products.

4.7 Prediction of food choice

When analyzing the relationship between the eye-tracker parameters and food choice, a new research question raised to be answered: which statistical model gives the most accurate predictions. The analysis of the applicability of the methods enables a deeper understanding of the above mentioned relationship.

In the first step of the data analysis, Relief-F and Fisher filtering feature selection methods (approaches applied to define a subset of relevant variables for use in model construction) were applied to identify the proper variables describing the connection between the dependent (consumers' choice as categorical variable) and independent (eye-tracking data as continuous and frequency) variables. After filtering, those variables were kept in the data analysis which were identified as important by both methods.

In the second step, the training and testing of thirteen prediction models was done. Their task was to predict consumer choices using the previously filtered variables. In order to create balanced data sets (balanced choice frequencies) for the prediction models, 1000 times bootstrap was applied on each product within a product group. Values of error rate, cross-validation results (minimum, maximum and average), prediction accuracy of each product in the group (upper right, upper left, bottom right and bottom left), bootstrapped error rate and results of leave-one-out cross-validation were computed to compare the performance of the models and to choose the superior one (the one having the best values of the parameters). The models task was to predict the choice based on gazing parameters for each product group as accurately as possible. All computations of the models were completed using Tanagra version 1.4.50 (Rakotomalala, 2005). The obtained results were then analyzed using SRD method.

Total dwell duration, fixation count and fixation duration were the three obtained variables after Fisher filtering and Relief-F feature selections. All the selected variables were significant in the models. The SRD analysis of the performance indicators revealed that the lowest SRD values were found for iterative dichotomiser 3 algorithm (ID3) (Figure 7.). It means that ID3 had the lowest error rates, cross-validation minimum, maximum and average values, bootstrapped error rate and leave-one-out cross-validation values.

Furthermore, its prediction accuracy for the four product alternatives was the highest among the tested models. On the second position, three models were found, cost-sensitive decision tree (CSMC4), Quinlan's C4.5 decision tree algorithm (C4.5) and random tree (RND). On third place was *k*-nearest neighbors algorithm (KNN). All the other models fell right to XX1 (5 % probability level), which means that their ranking cannot be distinguished from random ranking. Decision tree algorithms showed better performance, which could be due to their logic-based system. The predictor variables seem to have more logic than nonlinear, linear or instance-based connection with the chosen product.

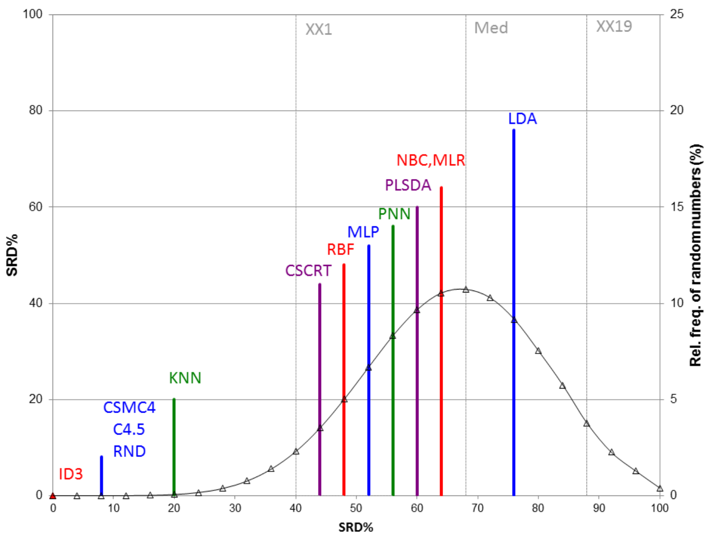

Figure 7. The scaled SRD values of the models based on the performance indices determined by sum of ranking differences. The best possible values of the indices (Read) were used as reference (benchmark) column. Scaled SRD values are plotted on *x*-axis and left *y*-axis, right *y*-axis shows the relative frequencies (black curve). Probability levels 5 % (XX1), Median (Med), and 95 % (XX19) are also given

5. NEW SCIENTIFIC RESULTS

1. I proved that parallel factor analysis (PARAFAC) and Tucker-3 methods are effective tools to build preference maps based on human sensory and instrumental data sets. The triplot of the built preference map combines the results of the panelists, the attributes and the products. Comparison of principal component analysis, PARAFAC and Tucker-3 methods was also introduced.
2. I introduced that nonlinear principal component analysis (PCA) of categorical ranking data is suitable to create preference maps of flavored kefir products. The generally applied PCA-based methods are inappropriate due to the nonlinear nature of the ranking data.
3. I proved that generalized pair-correlation method (GPCM) is a more effective tool to analyze just-about-right data than the generally applied methods. Two new plots, a bubble and a line plot, were invented to visualize GPCM results. These plots are used as decision supporting tools.
4. I proved that sum of rank-differences (SRD) method is able to create the significant ranking of JAR data analysis methods. Furthermore, I verified that GPCM gives the most precise results about the impact of JAR variables on consumer liking. This method is suggested instead of those proposed by ASTM MNL-63.
5. I proved that running SRD on a transposed matrix makes the approach suitable to evaluate more precisely the impact of JAR variables on consumer liking using multiple JAR data evaluation methods. This enables to give the directions of product development process based on the consensus of multiple methods which makes the results more reliable. This is even true if the methods of ASTM MNL-63 give contradictory results.
6. I proved that consumer choice can be sufficiently predicted based on the results of eye-tracking experiments of multiple product groups and the prediction models can be ranked based on their performance. This enabled to define the best models to predict consumer choice.
7. I proved that multivariate statistical models, using general eye-tracking variables, give more accurate prediction results compared to the generally applied last fixation.
8. I proved that the characteristics of consumer choices can be evaluated using survival analysis. I also introduced that consumers need significantly more time to choose one from certain product groups.

6. CONCLUSIONS AND SUGGESTIONS

During my PhD work, I answered puzzling questions of sensory analysis and sensometrics. However, the answers have risen further practical and scientific questions as well.

It is necessary to have the proper software background for running the introduced methods easily and to make them available for a broad range of users. This enables to run the whole sensory processes automatically on computers. A proper software support needs to ensure the interface to design experiments, sensory sheets, collect, clean, analyze and visualize data. This makes it easy to automatize processes; hence creating DOE becomes faster, computational errors are reduced and the error coming from the data input of paper based evaluation sheets is eliminated.

Today, there are several sensory evaluation software packages available (Compusense five, Fizz, RedJade, EyeQuestion, stb.), although these are expensive and closed-source software; hence the implementation of new methods is hard or even impossible. In contrast, the internationally available R-project software is free and ready to be used on sensory data. Integrating the advantages (sensory and data analysis software), an effective, open source, sensory evaluation focused program solution should be created. In my opinion, such a solution should be written on web based programming language, be platform independent (Windows, Android, IOS, Linux) to make it easy to run using solely a browser (*e.g.* Google Chrome, Mozilla Firefox, Opera *etc.*) on every platform (tablet, smartphone or computer) and support the whole sensory process. This approach enables the use of self-developed methods which could be optimized to the given industrial/commercial/research needs.

There are several research projects conducted about the connection between sensory instrumental measurements. In the literature, there are more and more publications which analyze the sensory attributes of food products using human sensory panels and instrumental methods together. The newest ones even introduce integrated approaches by combining the two.

Besides the applied eye-tracking device, which is capable to record the eye movements, other sensors can be integrated to monitor the face mimic, pupil dilatation, skin conductivity, pulse and brain waves in order to map our sensations about food products. Using these data, the connection between the signals of the sensors and the answers of consumers (OAL) can be modeled easily.

One drawback of JAR scales is that the lack of amounts in the results or with other words, how much should an attribute be changed to achieve better consumer acceptance. The only result is a direction in which the development should be made to get higher acceptance. Answering this question needs further research.

It has to be mentioned that among the scientific literature there is a lack of publications which uses JAR product development with multiple feedback to consumers based on the obtained preference. Hence it is unknown how many cycles of development is needed for certain product groups in a given consumer segment. To optimize the number of cycles, the definition of the balance point of overall liking (OAL) and the used resources is necessary. After a certain point, the development is not profitable, the OAL improves less and less but the expenses are increasing. If the only aim is to increase OAL, the first few cycle will significantly increase it but every cycle improves less and less. This means that the cycles should be repeated until it gives higher OAL values. In such cases, emphasis should be taken on the changes of the "just-about-right" group of the consumers.

Social media generates high amount of freely accessible data which can be analyzed using text mining and network analysis methods. These kinds of approaches are able to describe food preferences, consumer groups with special dietary needs and to analyze the connections between food/marketing tools and their judgement. A further advantage of such data is that food products were consumed in a natural environment and not in a sensory laboratory. Network analysis furthermore identifies opinion leaders (media personalities, nutritionists, athletes, physicians), who have a great influence on consumer habits.

PUBLICATIONS

<u>Articles in journals</u>

Journals with impact factor

1. V. Losó, A. Tóth, **A. Gere**, J. Heszberger, G. Székely, Z. Kókai, L. Sipos (2012): Methodology problems of the industrial preference mapping. *Acta Alimentaria,* 41 (Suppl) pp. 109-119. (IF=0,444).

2. A. Szőke, V. Losó, L. Sipos, A. Geösel, **A. Gere**, Z. Kókai (2012): The effect of brand/type/variety knowledge on the sensory perception. *Acta Alimentaria,* 41 (Suppl) pp. 197-204. (IF=0,444).

3. A. Györey, **A. Gere**, Z. Kókai, P. Molnár, And L. Sipos (2012): Effect of sample presentation protocols on the performance of a margarine expert panel. *Acta Alimentaria,* 41 (Suppl) pp. 62-72. (IF=0,444).

4. **A. Gere**, V. Losó, A. Tóth, Z. Kókai, L. Sipos (2012): Kukoricafajták preferenciatérképezése szoftveres támogatással. *Élelmiszervizsgálati közlemények,* 58 pp. 118-130. (IF=0,04).

5. L. Sipos, **A. Gere**, Z. Kókai (2012): Mesterséges ideghálózatok (ANN) alkalmazása az érzékszervi minősítés gyakorlatában. Élelmiszervizsgálati Közlemények, 58 pp. 32-46. (IF=0,04).

6. A. Györey, **A. Gere**, Z. Kókai, L. Sipos, P. Molnár (2012): Kenőmargarinok bírálatára kiképzett szakértői panel teljesítményének mérése. *Élelmiszervizsgálati Közlemények*, 58 pp. 47-59. (IF=0,04).

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