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Correlations between value-based segmentation and eye movements during a food choice task: Case study with breads

Keywords: eye-tracking; value-based segmentation; eye-movements; survival analysis; Gehan test

SUMMARY

Connections between eye-movements and self-reported values were analyzed in this study. Cluster analysis of self-reported values of 140 participants was performed using internal cluster validity measures and the obtained optimal number of clusters was six. Differences between clusters were found in decision times where eco-rationalists, who rated true friendship, comfortable life, environment and energy conscious life and economical living as highly important, needed more time to choose one from the three bread alternatives. These results were strengthened by the analysis of the eye-tracking variables which showed that members of the eco-rationalist and family-oriented clusters spent more time to gaze at the stimuli. Our results confirmed that there is a significant link between the self-reported values and eye-movements; hence it is advisable to split the participants into groups according to their self-reported values prior to eye-tracking in order to avoid false conclusions.

Introduction

Eye-tracking is a widely used technology to capture the eye movements of participants completing different tasks (*e.g.:* choice tasks, word association tasks, free viewing tasks, *etc.*). During the measurements, several eye-tracking parameters are recorded which later can be used to characterize the gazing pattern of the individuals. These results contain the gazing data of those regions of the presented stimuli which are in the focus of the studies, the so-called areas of interests (AOIs). The recorded gazing data contain the time to first fixation, which is indicative of the attentional capture of the AOI, and the order in which participants process them for completing the task. Fixation count is related to information processing and indicates the difficulty of visual processing **[1]**. Total fixation duration is calculated by summing up the durations of all the fixations within a single AOI. It shows how difficult is to extract information from the AOI [1]. Using these variables, gazing behavior can be used as an indicator of information processing. For this reason, eye-tracking methods have been widely used in sensory and consumer researches to uncover how consumers acquire information from nutrition labels, for example **[2]**.

However, there are several factors that influence gazing behavior. In addition to the typical experimental parameters (image quality, resolution, task type, *etc.*), it has been proven that gazing behavior can be participant dependent, too. The effect of fat content on visual attention and choice of red meat was analyzed in a recent study where significant gender difference was found **[3].** 40 male and 65 female participants were tested and it has been reported that female consumers payed more attention and required less time to choose meat products with lower fat content. On the other hand, males spent more time to look at meat products with higher fat content and needed more time to choose meat products with lower fat content.

Cultural differences can also cause diverse viewing patterns. Chinese and North American consumers were tested by presenting food pictures with different backgrounds. The authors reported that American participants looked at the food items

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faster compared to the Chinese group. Furthermore, Americans focused more on the food item and not on the background (*i.e.* tableware, decoration) and the number of revisits was also significantly higher in the case of Chinese participants **[4]**.

Not only gender or socio-demographic factors can affect gazing behavior, but psychological factors may also play a major role. Rational and intuitive thinking styles were compared and their effects on eye movements were analyzed in a study. In their paper, the authors used yogurt labels and the Rational Experimental Inventory questionnaire to map the thinking styles of the participants. After data analysis of the results, two major groups were identified. They concluded that consumers having analytical-rational thinking engaged on a greater information search and a more thoughtful analysis of nutritional information for making their choices than consumers who preferred intuitive-experiential thinking **[5]**.

The next step in understanding consumer gazing behavior is the analysis of the consumer's personal values. The term of "*value*" can be defined as "*an enduring prescriptive or proscriptive belief that a specific end-state of existence or specific mode of conduct is preferred to a different end-state or mode of conduct for living one's life*" **[6]**. Value based segmentation is typically used by market players to identify people's motives and their behavior. Such motives can be the attachment of consumers to food category attributes, such as sustainability and healthiness, *etc.* **[7]**. Values are typically measured on grid-style scales which consist of different set of terms (*e.g.:* friendship, family, *etc.*). Participants are asked to mark how important the given value is for them using Likert-scales. Euard Gabele **[8]** was the first in this area to measure the values using differential scales. The scale, developed by Hartman (1981), was based on these and contained 32 values. This scale proved to be too long for the participants and therefore Windhorst (1985) shortened it and introduced a simplified Hartman scale which is in closer relationship with the consumption.

Although there are several studies investigating the factors influencing eye movements, there is a lack of studies focusing on the differences coming from the self-reported values of the individuals. In order to fill this gap, the aim of this research is to find correlations between value-based segmentation and eye movements during a food choice task.

Materials and methods

Questionnaire

The Windhorst (1985) scale was used and the task of the participants was to rate their agreement with the items from 1 (not important) to 5 (very important). The Hungarian translation of the following list of values was applied **[11]**: alternative/not traditional lifestyle, family life, health consciousness, enjoyable life, caring about culture and arts, traditions, true friendship, good appearance, comfortable life, environment and energy conscious life, working for the community, high living standards, education, self–realization, having a lot of free time, personal and financial security, personal freedom/independence, economical living, social recognition and social origin.

Eye-tracking measurement

The measurements were carried out in the Sensory Laboratory of the Department of Postharvest and Sensory Evaluation at Szent István University, Hungary, and students were asked to participate in the study. A total of 150 students (56 male and 94 female aged between 18 and 45) participated, but after checking the recorded data, 10 participants had to be excluded due to different reasons. The eye-tracker was placed in a completely white sensory booth located in a quiet room and disturbing factors were minimized. A Tobii Pro X2-60 screen-based eye tracker (60Hz) and Tobii Studio software (version 3.0.5, Tobii Technology AB, Sweden) were used to present the stimuli and to analyze the gazing behavior of the participants. Stimuli were presented on a calibrated CRT monitor, calibration was performed using an X-rite Eye-One pro device. The display of the eye-tracker is calibrated as sRGB (gamma=2.2, CCT=6500 K) CRT monitor, (Samsung SyncMaster 757 MB, SN: PU17HSAX907276V). The stimulus images were shown on the eye-tracker display (17 in., 1280 × 1024 pixel resolution, 75 Hz).

Prior to the test, all participants were informed about the procedure and that their gazing behavior would be recorded. In the first step, participants were asked to fill out the Windhorts-based questionnaire (see details in section 2.1 Questionnaire). After this, they sat down in front of the calibrated monitor in a relaxed way and placed their dominant hand on the computer mouse. The recordings were started after a successful calibration of the eye-tracker. During the eye-tracking measurements, the following four parameters were recorded **[12]**:

1) Fixation Duration (FD): length of a fixation in seconds.
2) Fixation Count (FC): number of fixations on a product.
3) Dwell Duration (DD): time elapsed between the user's first fixation on a product and the next fixation outside the product in seconds.
4) Dwell Count (DC): number of "visits" to an Area Of Interest (AOI).

Choice task

A three-alternative forced choice paradigm (3AFC) without time limit was used based on the method presented by Gere and co-workers (2016). Two choice sets were presented consisting of pictures of

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two and three product alternatives. The first set of two alternatives was used as a warm-up to familiarize the participants with the procedure. It was not included in the data analysis because several participants made mistakes while completing the choice task. The remaining choice set presented breads. The process is demonstrated in **Figure 1**. Between the pictures, a black fixation cross was presented for 3 ms to standardize the starting point of the gaze. Products were chosen based on their familiarity and liking ratings, according to a pilot study with 70 students (equal gender and age distribution as for the main study). The participants had to choose the product that appealed most to them without time limit.

Data analysis

Agglomerative hierarchical clustering and k-means clustering was performed in order to create consumer clusters based on the self-reported values of the 140 participants. Clustering indices were used to determine the proper clustering algorithm and to establish the suitable number of clusters. The following indices were applied: Silhouette index, Calinski-Harabasz index and Dunn index **[14]**. Clustering and calculation of clustering indices were carried out using R-project (R-3.2.3), cluster, stats and clusterCrit packages **[15]**. Survival analysis was applied to uncover the differences between the decision times of the created clusters. Comparison of eye-movement data (FD, FC, DC and DD) of the clusters was performed using the Kruskal-Wallis test. Normality tests were run using XL-Stat software Version 2014.5.03 (Addinsoft, Paris, France) while survival analysis was run in StatsSoft Statistica 8.0 (Tulsa, OK, USA).

Results

The areas of interests (AOIs) were defined as shown in **Figure 2a**, each bread sample represented one AOI. The gazing behaviour of each participant was recoreded separately which enabled the analysis of the result of each participants independently. Gazing behaviours of the participants were plotted and the order of their gaze showed which product was first glaced at **(Figure 2b)**. Participants started viewing the stimuli from the midpoint due to the presented fixations cross. Analysis of the individual results helped to identify insufficient eye-tracking quality and data (fixations otside the stimulus, participants looking away from the screen). After removing all the identified insufficient recordings, the gazing data of the remaining 140 participants were plotted and analyzed toghether **(Figure 2c)**. In order to make the figures easier to understand, a heat map was generated using the data of Figure 2c, in which warmer colors indicate the fixation dense parts of the presented stimulus.

In the first step, clusters were created based on the data of the Windhorst questionnaire. There is no direct information in the literature about the best performing clustering algorithms, hence several agglomerative hierarchical clustering (AHC) and k-means clustering werre run. 2-10 clusters were created based on the followings. During AHC, the following measures were applied to create the distance matrices: Euclidean, squared Euclidean, Manhattan, Canberra, binary and Minkowski. For each distance, the following agglomeration methods were computed: Ward, single, complete, average, McQuitty, median and centroid. After this, *k*-means clustering was also run on the data. The clustering solutions than were tested using Silhouette, Calinski-Harabasz and Dunn clustering indices. In the case of all three clustering indices, the higher value means better clustering performance. Since all the applied indices are internal clustering criterions, the proper way to use them is to compare clustering solutions obtained on the same data. These solutions should differ either in the number of clusters or in the clustering method used. After analyzing all the computed solutions, the six cluster solution of squared Euclidean distance with Ward's method proved to be the best performing one (Silhouette index: 0.91, Calinski-Harabasz index: 9.68, Dunn index: 0.24). One interesting result is that there was no difference in the gender distributions of the clusters (χ^2 (5, N = 140) = 2.91, p = 0.714) **(Table 1)**.

Based on the results obtained, participants can be classified into 6 different groups based on their rated values. In the next step, the clusters obtained were characterized. The normality tests of the variables (using the Shapiro-Wilk test) showed that the data set follows a normal distribution (p>0.05) in the case of all variables, while the Levene test showed the homogeneity of the variances to be equal. This enabled the use of one-way analysis of variance (ANOVA) which can assess if there are significant differences between the clusters based on their self-reported values **(Table 2)**.

Members of cluster 1 prefer the alternative lifestyle and it is really important for them to express themselves hence they will be called in the following as open-minded. For cluster 2, the main values are true friendship, comfortable life, environment and energy conscious life and economical living, creating the group of eco-rationalists. Cluster 3 contains the conservative-traditional particpants because the most important values were family life, traditions and working for the community. Cluster 4 is the group of hedonic-independent people because the highest values are enjoyable life, true friendship, personal and financial security and personal freedom/ independence. The highest mean values were found in the case of cluster 5, making them the group of dedicated–quality-oriented persons due to their high values of health consciousness, enjoyable life, caring about culture and arts, good appearance, high living standards, education, having a lot of free time, personal freedom/independence, social recognition and social origin. Members of cluster 6 rated as very important the following values: enjoyable life, family life and having a lot of free time which makes them the group of family-oriented people.

Decision times of the created clusters were compared using survival analysis. Survival analysis compares the cumulative proportion of survival (decision making) of the clusters as a function of time. The obtained Kaplan-Meier survival plot is generated by plotting the time on the *x*-axis and the proportion of those participants who made their decisions on the *y*-axis **(Figure 3)**. Shorter decision times thus result in steeper curves. Figure 3 shows that eco-rationalists needed the longest time to choose one product from the three alternatives. On the other hand, traditionalists needed the least time to choose.

For the survival data recorded for the participants, null hypothesis testing (two samples are from populations that follow the same survival function) can be performed using Gehan's generalized Wilcoxon test. Hence, in order to statistically compare the results of survival analysis, Gehan's Wilcoxon test was applied for pairwise comparison of the survival functions. Significant differences were found between open-minded people and eco-rationalists. Furthermore, eco-rationalists needed longer time to choose compared to the conservative-traditional and dedicated–quality-oriented groups. The fastest decision makers were members of the conservative-traditionals group who made their decisions significantly faster than hedonic-independent, dedicated–quality-oriented and family-oriented people **(Table 3)**.

In the final step of the data analysis, the relationships between the gazing parameters and the created clusters were analyzed. After normality check, the applied Shapiro-Wilk test showed that none of the eye-tracking variables follow normal distribution, thus the non-parametric Kruskal-Wallis test was applied to test the differences between the six created clusters based on the eye-tracking variables. As a *post hoc* test, the Conover-Imam test was used, which is similar to Dunn's method, but is based on a Student distribution. It corresponds to a *t*-test performed on the ranks (Table 4). Based on the results, the eco-rationalist and family-oriented groups spent more time gazing at the stimuli. They had longer total fixation and dwell values as well as more fixation and dwell counts compared to the other groups.

Fixation duration and count describe how complicated it was for the consumers to process the information [1]. It follows that longer total fixation duration means that eco-rationalists and family-oriented people spent more time on the AOIs of the pictures. Dwell durations are defined as the time elapsed between the user's first fixation on a product and the next fixation outside the product, thus a longer dwell duration means a higher attention capture. The lowest values were recorded in the case of conservative-traditionals, which confirms the results of the survival analysis, namely that they not only needed less time to choose one sample from the three alternatives but they also spent less time looking at the images.

Based on the previous results of the authors, choice was predicted using multivariate classification algorithms, which can be used to describe the relationship between eye movement variables and stated food choise. Earlier results showed that the chosen alternative received higher visual attention **[12,16,17]** and that eye movement data predicted choice well **[13]**. However, in our case, a three alternative forced choice situation is used which uses a triangle arrangement of visual stimuli. Triangle arrangement differs from the earlier square arrangement of four products in a way that it has one product on the top and additional two on the bottom of the screen, creating an assymmetric presentation of the stimuli. The authors hypothetised that the assymmetric arrangement might cause differences in choice prediction.

In order to ensure balanced group sizes for the classification models, bootstrapping was applied to create 100 cases for each three choice alternatives. The new data table was used by linear discriminant analysis (LDA), partial least squares discriminant analysis (PLS-DA) and classification and regression trees algorithms (CART) to predict the choice based on the eye movement data. Eye movement data consisted of the fixation and dwell durations and counts recorded on the alternatives.

The obtained results showed that PLS-DA gave 84 % cross validation accuracy, while LDA showed only 65 %. The highest cross-validated prediction accuracy was achieved, however, by the CART model, with a prediction accuracy of 93.33%. These results support our earlier findings, namely that the connection between eye movement variables can be best described by decision trees. It also suggests that this connection can be best described by logic-based approaches rather than other methods.

Conclusions

Our results confirmed that there is a significant relationship between self-reported values and eye-movements, thus it is valuable to split the participants based on their self-reported values prior to eye-tracking in order to avoid false conclusions. Major differences were found between the decision times of the created clusters. In the future, other food groups should be analyzed to ensure that these differences are stable across other products. The stability of the clusters should be tested using different numbers of product alternatives. In order to validate the clusters described, other consumer segments should be tested (*e.g.*: retired people, children, neophobic consumers, consumers with special nutritional needs, *etc.*).

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