Investigating the effect of the Nutri-Score label using facial analysis and eye-tracking technology

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Abstract

The examination of front-of-pack nutrition labels is essential as manufacturers can choose from several labelling options. Understanding which labels best support consumer decision-making requires further investigation. In this study, 20 food products featuring Nutri-Score labels were used as visual stimuli. A total of 71 participants took part in the study. Their eye movements were recorded using an eye-tracker and their emotional responses were analyzed with facial expression recognition software to explore the relationship between the products and the elicited emotions. The results revealed significant differences in two of the six basic emotions - happiness and surprise - and identified products capable of eliciting both. Participants did not always display surprise when their responses were incorrect. The findings also suggest that the Nutri-Score label may be difficult for consumers to interpret, as indicated by the frequent display of surprised expressions.

Keywords: Nutri-Score label, eye-tracker, facial expression, consumer decision-making, choice

INTRODUCTION

During shopping, while standing in front of the shelves, consumers are exposed to countless pieces of information, all of which influence their decisions. In many cases, these decisions are made without prior information (Szakál et al., 2023). Given the importance of the food industry at a global level, the analysis of factors influencing purchase intentions is crucial (Peters-Texeira & Badrie, 2005). Studies on the impact of food packaging on consumers' purchase decisions have shown that food selection in stores is a complex process, determined by both sensory and non-sensory characteristics (Gelici-Zeko et al., 2012). Given this, consumer perception of packaging is essential, especially for food products where consumers must choose between relatively similar items (Gómez et al., 2015). By understanding how consumers perceive, evaluate and choose food, the industry can optimise packaging design and create added value that can contribute to the brands' business strategies (Rundh, 2016).

Front-of-pack labels

Nutritional information is typically found on the back of packaging; however, the use of front-of-pack (FoP) labels is becoming increasingly common. These labels can greatly assist consumers in decision-making by providing key nutritional information in a simplified format (Godden et al., 2023). FoP labelling is also advantageous from a consumer perspective because the information on the back of the package is often difficult to interpret and shoppers rarely consult elements such as the nutrition facts table during the few seconds available in a typical shopping situation (Machín et al, 2023).

Regulation (EU) No 1169/2011 provides detailed information on where, how and what information about a food product should be displayed on packaging. However, it does not set strict rules regarding the use of FoP labels, which are voluntary and are typically placed in the main field of vision (Regulation (EU) No 1169/2011 on the provision of food information to consumers). As a result, manufacturers have a wide range of FoP labels at their discretion. FoP labels can be grouped into three categories. Non-directive labels simply display the amount of key nutrients in the product, leaving consumers to interpret the healthiness of the food, as in the case of the GDA (guideline daily amount) label. Semi-directive labels provide an overview of the nutrient content while also evaluating nutrient levels using visual aids such as colour schemes; a typical example is the MTL (multiple traffic light) label. Directive labels, on the other hand, typically do not reveal the nutrient profile of the product, reducing the consumer's cognitive effort by eliminating the need to interpret complex information or form a comprehensive picture of the nutrient quality of the product (e.g. Nutri-Score label) (Gabor et al., 2020, Szakál et al., 2024).

The Nutri-Score indicates the overall 'nutritional quality' and 'healthiness' of a food in relation to the benchmarks set by the Nutrient Profile Model developed by the Food Standards Agency (FSA) (van Der Bend et al., 2022; Dervishi & Dohle, 2025). The Nutri-Score label uses a five-level scale to indicate the 'nutritional quality' and 'healthiness' of a food, ranging from A to E, with corresponding colours from dark green to red. Foods of higher nutritional quality are labelled dark green A, while those of lower quality receive a red E (Dervishi & Dohle, 2025).

Emotion recognition

First, it is important to distinguish between emotions and feelings, as these concepts are not synonymous, although they are closely related. Both represent reactions to stimuli that evoke internal responses. According to Oatley and Jenkins (2001), emotions are generally triggered by a person's conscious or unconscious evaluation of an event as relevant to a significant concern. An emotion is perceived as positive if the event supports the concern and negative if it obstructs it. Feelings, on the other hand, are responses to emotions. They depend on mental associations formed by the brain based on past experiences, memories and thoughts (Cookson, 2015). Emotions have long been a subject of human curiosity, studied for centuries from philosophical, scientific, artistic and literary perspectives. Throughout human evolution, emotions have played a critical role in survival and the efficient functioning of society. Unlike reflexes, emotions evolved because they facilitated adaptation to a constantly changing environment (Gračanin & Kardum, 2008). They were crucial, for example, in finding food, water and shelter, protecting offspring, avoiding danger and escaping from life-threatening situations (Šimić et al., 2021). Furthermore, the ability to recognize and communicate emotions supports empathy, relationship-building, successful social interactions, effective communication, problem-solving, the development of social and emotional intelligence, conflict management and mental well-being (Ekman, 2007).

Across various disciplines, several theories attempt to explain the origin and functioning of emotions, including the relationship between an individual's behaviour and their environment (Coppini et al, 2023). Categorical models of emotion define emotions as discrete categories, often referred to as primary or basic emotions, with many models identifying six core types (Mehrabian, 1997). Ekman (1970) identified six universal emotions exhibited by all humans: happiness, sadness, anger, fear, surprise and disgust. However, a seventh emotion, neutral, should not be overlooked.

The analysis of facial movements used to be based on observation alone, but today, emotion recognition software offers digital support for more accurate analysis. In human communication, 55% of the message is conveyed through facial expressions, 38% through tone of voice and only 7% through verbal communication (Mehrabian, 1971). Facial expressions play a crucial role in conveying changes in affective states (Pollak et al, 2009). When a facial expression is identifiable as a specific emotion, it communicates the individual's feelings and provides social information (Rinn, 1984). The best-known approach to facial expression research is the Facial Action Coding System (FACS), which allows researchers to identify the emotions conveyed by participants by distinguishing facial muscle movements (Pos & Green-Armytage, 2007). The basic theory underpinning FACS has been widely applied in research to support the identification of emotions, and various techniques have been developed to improve the accuracy of recognition. In the field of design, studies have indicated that adopting facial expressions as a reference can be effective in design. More recent research has suggested that human facial expressions may guide designers in responding to specific colours and colour combinations (Pos & Green-Armytage, 2007). It has also been argued that colour information can improve facial expression recognition due to the complementary characteristics of image textures (Lajevardi & Wu, 2012). Overall, facial expression recognition has been considered by many researchers to be more effective than other emotion recognition methods, such as speech, for interpreting a person's emotions (Pantic & Patras, 2006).

The Noldus FaceReader software can automatically analyse facial expressions associated with different emotional states and allows researchers to quantitatively analyse participants' facial expressions. Recent studies have shown that the software is an effective tool for analysing emotions, with an accuracy rate of 90% (Zaman & Shrimpton-Smith, 2006). Previous studies suggest that the emotional states identified by FaceReader can provide an immediate picture of participants' emotions. However, the software is limited to detecting only the six basic emotions and a neutral state; more complex emotions cannot be identified. Zaman and Shrimpton-Smith (2006) found that participants started their experimental task with seriousness, but FaceReader classified their emotion as anger. Furthermore, the neutral emotion during the experimental condition may have been misinterpreted as sadness due to the camera angle. Since the duration of each emotional expression is short, ranging approximately from 0.5 to 4 seconds (Ekman, 2004), it becomes challenging to quantify differences between data points, and not every frame of the participant's video may be analyzed (Cohen et al., 2013). The software has a very wide range of applications. For example, Bartkiene et al. (2021) investigated the impact of different origins of dark chocolate on consumers' emotions, their overall acceptability, and the relationship between emotions and the physico-chemical properties of chocolate. Berčík et al. (2024a) investigated the impact of the Nutri-Score label on consumer choice. The software has also been used in marketing research, for example, to investigate cognitive preferences influenced by scents in the bakery product category in the Slovak and Spanish markets (Berčík et al., 2024b). Similarly, Tzafilkou et al. (2023) analyzed emotional changes induced by social media video campaigns on food products during online shopping. In addition, the software has found applications in the field of medicine (Obayashi et al., 2021; Rutter et al., 2022; Dorante et al., 2023; Kollar et al., 2024) and in various areas of economics (Lewinski, 2015; Saraiva & Gonçalves, 2023; West et al. 2023; Zhang et al., 2023). It is also a popular research tool in psychology (Comes-Fayos et al., 2024; Martin et al., 2024; Fattal et al. 2024) and the social sciences (Drăgan & Fârte, 2022; Ma et al., 2025).

Eye-tracker

Eye-tracking technology enables the measurement and analysis of consumer behaviour based on eye movements. The method used in eye-tracking studies is pupil centre corneal reflection (PCCR). Light enters the eye through the pupils and is reflected by the cornea. To measure the position of the pupil, the eye-tracker uses near-infrared light, which is invisible to the human eye (λ= 0.75-1.4 μm). An eye-tracker consists of three main components: cameras, a near-infrared light source and algorithms to calculate the exact gaze point of the participant. The near-infrared light creates an infrared reflection on the participant's eyes which is captured by high-resolution cameras. These images of the eyes along with the near-infrared light reflections are analysed by algorithms to determine the position of the eye and gaze direction. The method is highly unobtrusive and requires minimal effort from the participants (Danner et al., 2016). The use of the eye-tracking is widespread across various disciplines. In psychology, it provides insights into reading processes (Steinfeld, 2016), differences in social interaction such as those in autism or schizophrenia (Falck-Ytter, 2015), and the study of emotional functioning (Ng and Hort, 2015). It is also employed in computer software testing (Goldberg & Wichansky, 2003) and by media designers and marketing professionals to optimize the delivery of information and maximise consumer impact (Almeida et al., 2016).

The aim of the research was to determine whether there is an interaction between the products in the study and the participants' emotional responses. In addition, the study aimed to determine whether an eye-tracking parameter (FD, fixation duration) could predict participants' choices.

MATERIALS AND METHODS

Location

The measurement was carried out at the Buda Campus of the Hungarian University of Agricultural and Life Sciences, in an 18 m^2 room located in a quiet but central part of the campus. This location was advantageous, as it facilitated participant recruitment for the studies, while still allowing the measurements to be conducted undisturbed. A table with a computer was placed in the centre of the room. The room was illuminated by an LED panel (6500 K, 1600 lm) mounted on the ceiling above the table.

Participants

Participant data were collected after the measurement using a pre-designed Google Forms questionnaire (Google LLC, California, USA).

A total of 71 volunteers (28 men and 43 women) participated in the study. The recruited participants were Hungarian (40) and foreign (31) students and staff members of the Hungarian University of Agricultural and Life Sciences. As a result, the majority of participants were between 18 and 24 years of age.

FaceReader software

The Nutri-Score label was tested using the FaceReader version 9.1, developed by Noldus Information Technology (Wageningen, The Netherlands), in addition to the eye-tracker. FaceReader is a facial analysis software designed to recognise facial expressions. The software has been trained to classify participant's facial expressions into one of the categories described by Ekman as basic emotions: happiness, sadness, anger, surprise, fear, disgust and neutral (Ekman, 1970). The software can classify facial expressions either live, using a webcam, or offline, using video files or images. In this study, videos of the participants' faces were captured using a Lenovo ThinkPad L15 laptop camera with 720p HD resolution.

The software operates in three steps (Kuilenburg et al., 2005):

1. Face recognition using the Viola-Jones algorithm.
2. Accurate modelling of the face using an algorithmic approach based on the Active Appearance Model described by Cootes and Taylor. The model maps more than 500 key points on the face and captures the texture enclosed by these points. The key points include the outline of the face and the distinctive facial features, such as lips, eyebrows, nose and eyes. Texture is an important component as it provides additional information about the state of the face. While key points describe the position and shape of the face, they do not capture details such as the presence of wrinkles or the shape of the eyebrows. However, these points serve as reference markers for classifying facial expressions.

3. Classification of facial expressions is performed using artificial neural networks trained on more than 10.000 manually annotated images.

Eye-tracker and software

The eye-tracking procedure followed the guidelines published by Fiedler et al. (2020). In the study, eye movements were tracked and recorded using Tobii Pro Fusion (Tobii Pro AB, Danderyd, Sweden) desktop eye-tracker. Image sequences were presented using Tobii Pro Lab (Tobii Pro AB, Danderyd, Sweden) software version v.1.232.527.

Visual stimuli

A total of 20 commercially available foods were tested. During the measurement, video recordings were made to allow for analysis using Noldus FaceReader software (Wageningen, The Netherlands). Participants gave their consent for video recording by signing a declaration. The products included in the measurement included: Alpro Shhh…This is not milk; Venus Light salted margarine; Garden Gourmet vegan schnitzel; Gullón ZERO sugar free fibre biscuit; ZOTT Jogobella strawberry with live cultures; Venus natural baking margarine; HELIOS strawberry extra jam; Magyar ESL fresh milk; Nescafé Dolce Gusto latte macchiato coffee capsules; Coca-Cola Light carbonated soft drink; Nestlé Chocapic cereal; Alpro sugar free almond drink; Knoppers Nut Bar chocolate bar; Eisberg French garlic salad dressing; Diablo white chocolate cream; Nesquik Extra Choco cocoa drink powder; Nescafé Dolce Gusto flat white coffee capsules; Kania ketchup with basil and oregano; Nestlé Fitness strawberry cereal bar and Ritter Sport milk chocolate with whole hazelnuts. The abbreviated product names and their Nutri-Score classifications are given in Table 1.

Table 1. Abbreviated names and Nutri-Score classifications of the products used in the measurement. The Nutri-Score designations were established in 2023, the calculation methodology has changed since then, so the values in the table may differ from the current classification.

The name of the product	Abbreviation of the product name	Nutri-Score classification of the product
Alpro Shhh…This is not milk	milk	A
Venus Light salted margarine	margarine	D
Garden Gourmet vegan schnitzel	vegameat	A
Gullón ZERO sugar free fiber biscuit	biscuit	B
ZOTT Jogobella strawberry yoghurt with live cultures	yoghurt	B
Venus natural baking margarine	margarine2	D
HELIOS strawberry extra jam	jam	B

Magyar ESL fresh milk	milk2	E
Nescafé Dolce Gusto latte macchiato coffee capsules	coffee	B
Coca-Cola light carbonated soft drink	cola	B
Nestlé Chocapic cereal	chocapic	A
Alpro sugar free almond drink	alpromilk	A
Knoppers Nut Bar chocolate bar	knoppers	E
Eisberg French garlic salad dressing	dressing	C
Diablo white chocolate cream	spread	D
Nesquik Extra Choco cocoa drink powder	cocoapowder	A
Nescafé Dolce Gusto flat white coffee capsules	coffee2	D
Kania ketchup with basil and oregano	ketchup	D
Nestlé Fitness strawberry cereal bar	mueslibar	C
Ritter Sport milk chocolate with whole hazelnuts	rittersport	E

Process

As a first step, participants were asked to take a seat in front of the computer. The eye-tracker was introduced and the operation of both the eye-tracker and FaceReader software was explained. Based on this information, subjects who agreed to continue with the study signed a consent form. They were then reminded not to change their posture during the measurement, avoid turning their head and refrain from looking at the keyboard or mouse during the procedure. Following the briefing, the eye-tracker software performed a 9-point calibration. During calibration, participants were asked to follow a moving point on the screen with their eyes as it moved up, down, right and left, decreasing and increasing in size. After successful calibration, the timeline part of the measurement started, as partially illustrated in Figure 1. The first slide of the timeline displayed an informational text summarising the information about the measurement procedure and the tasks to be performed. After reading the text, participants pressed a key on the keyboard to proceed to the next slide, which presented a fixation cross in the top right-hand corner. The fixation cross was visible for only 2 seconds before transitioning to the next slide, which contained the first visual stimulus. For each product, a photo of the item was displayed, with the 5 Nutri-Score labels (A, B, C, D and E) displayed below it, as shown in Figure 1. For this slide, participants were asked to decide which Nutri-Score rating the product should receive based on the product photo. After selecting their answer by clicking on the chosen label with the mouse, they pressed a key on the keyboard. The correct Nutri-Score label for that product then appeared next to the image. Once the correct answer was displayed, the participant pressed another key to continue. A fixation cross appeared for 2 seconds on the screen before the second product and its correct label were presented. The process was repeated for all 20 products ending with a final slide that displayed a "Thank you for participating" message.

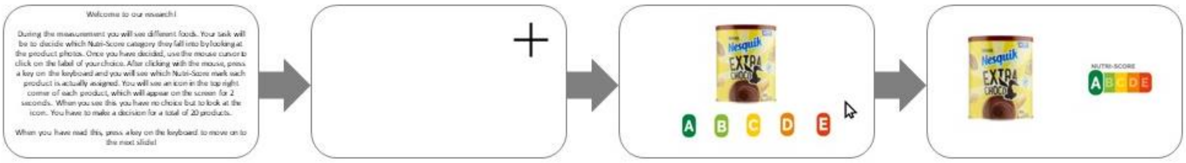

Figure 1. Extract from the timeline used in the measurement. The first slide contains the informative text, the second slide contains the fixation cross, the third slide asks the participants to choose the appropriate Nutri-Score classification for the product and the fourth slide shows the correct answer.

Data analysis

The data obtained from the FaceReader and eye-tracker during the Nutri-Score tagging task were analysed separately.

From the FaceReader software, only data retrieved from the post-choice page, (i.e. after participants made their selection) were included in the analysis. First, the data were analysed using analysis of variance (ANOVA), to identify which emotions showed statistically significant differences. This analysis was performed for each of the 20 tested products. Only those emotions that demonstrated significant difference were further analysed. Subsequently, a repeated measures analysis of variance (RMANOVA) was conducted to examine the interaction between product and emotional response. Both ANOVA and RMANOVA were performed using XLSTAT software, version 2023.2.1414 (Lumivero LLC., Denver, Colorado, USA).

Subsequently, the analysis of the eye-tracking parameter fixation duration (FD) was also performed to predict participants' choices using the Random Forest (RF) decision tree statistical method. Finally, the proportion of participants who correctly identified the Nutri-Score label for each product was assessed. The study also examined which predefined Areas of Interests (AOIs) were considered by those who made the correct choice during the decision-making process. These analyses were carried out using Microsoft Excel (MS Office, Washington, USA).

RESULTS

Testing the significance of emotions using analysis of variance

The results of the analysis of variance (ANOVA) for each emotion are presented in Table 2. The results indicate that of the six basic emotions and the neutral state, only happiness and surprise show significant differences. The other emotions did not demonstrate significant variation and were therefore excluded from further analysis. The remainder of this section presents the results from the FaceReader data analysis focusing on the emotions happiness and surprise.

Table 2. Analysis of variance (ANOVA) results for each emotion

Emotions	**Neutral**	**Happiness**	**Sadness**	**Anger**	**Surprise**	**Fearness**	**Disgust**
Pr > F	0.625	**0.001***	0.985	0.923	**0.000***	0.644	0.989

Bold and asterisk (*) indicate a significant effect at p<0.05.

Exploring the interaction between products and two emotions

The interaction between the 20 products and the two emotions (happiness and surprise) was tested by repeated measures analysis of variance (RMANOVA).

The results of the analysis of the interaction between the emotion happiness and the products are illustrated in Figure 2. The figure clearly shows that the product that elicited the most intense joy and happiness was Magyar ESL fresh milk. In addition, Coca-Cola Light carbonated soft drink, Nestlé Chocapic cereal, Nesquik Extra Choco Instant cocoa drink powder and Ritter Sport milk chocolate with whole hazelnuts elicited strong emotional responses.

In the case of Ritter Sport Milk Chocolate with Whole Hazelnuts, the emotion happiness may be attributed to two factors: first, participants likely expected that chocolate would be labelled as Nutri-Score E; second, it was the final product in the sequence, and by that point, participants may have become more confident in identifying the correct answer.

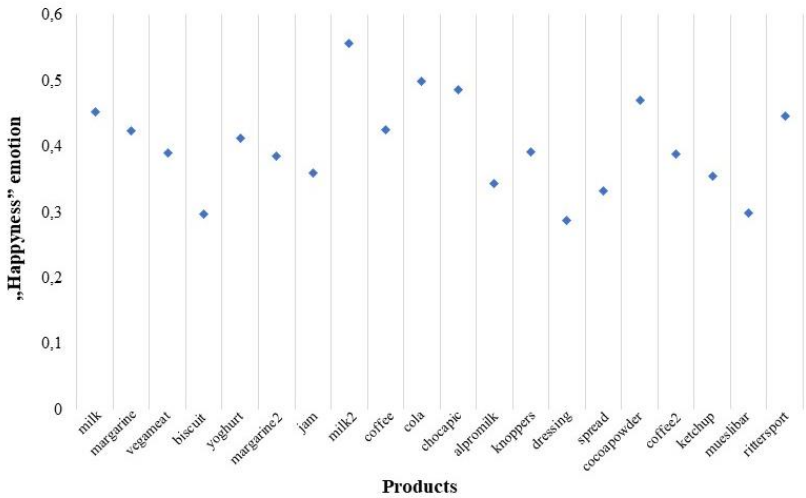

Figure 2. Representation of the interaction between the emotion happiness and the products based on RMANOVA analysis.

The results of the analysis of the interaction between the emotion surprise and the products are illustrated in Figure 3. The figure clearly shows that the products most intensively triggering feelings of surprise were Magyar ESL fresh milk, Coca-Cola Light carbonated soft drink, Nestlé Chocapic cereal, Nesquik Extra Choco Instant cocoa drink powder and Alpro NOT MILK oat drink.

In the case of Magyar ESL fresh milk, several respondents reported being surprised that the product received the lowest possible rating, i.e. it was rated Nutri-Score E, which led some to reconsider its future consumption. In contrast, the high ratings of Coca-Cola Light carbonated soft drink, Nestlé Chocapic cereal and Nesquik Extra Choco Instant cocoa drink powder surprised participants in a different way, as two Nestlé products received a Nutri-Score A and Coca-Cola Light was rated Nutri-Score B. Despite being marketed as a light product, most participants expressed surprise at Coca-Cola Light receiving such a favourable rating.

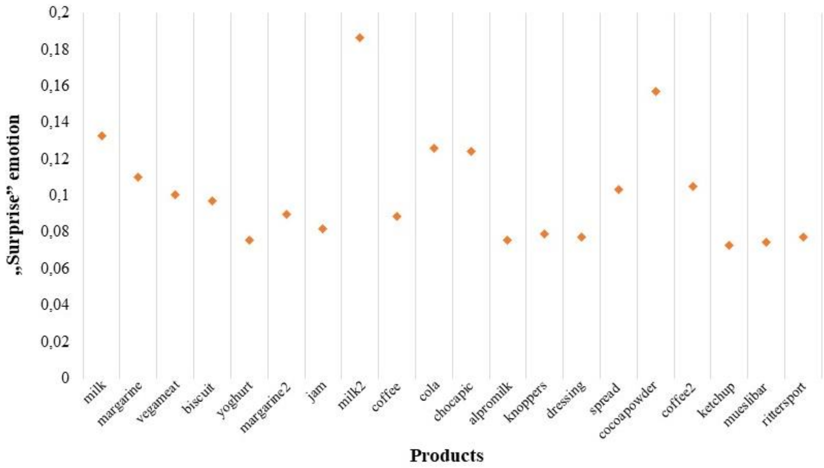

Figure 3. The results of the analysis of the interaction between the emotion surprise and the products after RMANOVA analysis.

Hungarian ESL fresh milk, Coca-Cola Light carbonated soft drink, Nestlé Chocapic cereal and Nesquik Extra Choco Instant cocoa drink powder evoked both happiness and surprise in participants. This may be attributed to the tendency of some participants to respond to surprising stimuli, in this case visual cues, with laughter or smiling, rather than a typical expression of surprise. Additionally, in unfamiliar setting and the nature of participating in the study may have influenced participants' emotional reactions.

Choice prediction

Among the eye-tracking parameters, the fixation duration (FD) was analysed to predict participants' choices. For this purpose, the Random Forest (RF) decision tree statistical method was applied. Among the eye-tracking parameters, FD is considered the most relevant parameter for describing the degree of visual attention that a given product attracts, as it provides information on the time participants' gaze lingers on a given visual stimulus. Therefore, the RF method based on this parameter was deemed appropriate. FD data were retrieved for the five Nutri-Score labels (A to E) from the eye-tracker software by assigning each label to an Area of Interest (AOI). Subsequently, it was determined whether each participant correctly identified the Nutri-Score classification for each product. The analysis then focused on the data of participants who correctly selected the Nutri-Score label for each product. Further examination was conducted to determine how many Nutri-Score labels were viewed by these participants before making their decisions. This helped assess the relative ease or difficulty of making a decision for each product. Table 3 presents the number of AOIs (AOI-1, AOI-2 and so on) viewed by participants before arriving at a decision for each product. The last two columns show the results obtained by the RF analysis. The column labelled RF (%) shows how well the RF model performed, i.e. specifically its prediction accuracy based on the confusion matrix. For example, in the case of Alpro sugar-free almond drink, the algorithm correctly predicted 90% of the observed classes - the highest accuracy of all products. And the RF val (%) column indicates the validation accuracy of the RF model. As expected, validation accuracy is generally lower than that of the training dataset. From the AOI summary data in the table, it is evident that a total of 46 participants correctly determined the Nutri-Score classification of the Alpro sugar-free almond drink based solely on the product image. Of these, 34 participants were able to determine at first glance which label they would like to choose, focusing on a single AOI (AOI-1), which contained the correct answer. This represents nearly half of all participants, indicating that this product was the easiest to classify correctly. In the case of Venus baking margarine, although nearly half of the participants guessed its Nutri-Score classification, only six individuals immediately identified the correct label. Some participants considered all five Nutri-Score options before making a decision. The table also shows that only a few products required participants to consider all five Nutri-Score labels, although in the case of the Alpro NOT MILK oat drink, three participants did so. A similar pattern was observed for those who viewed four labels. The visual inspection of the three labels did not show any significant difference from the visual inspection of the four and five tokens, however, Kania ketchup with basil and oregano had five participants who considered three options before deciding. Most participants, however, looked at only one or two labels before making a decision. It is likely that participants who hesitated between two labels found it difficult to distinguish closely related Nutri-Score categories. This suggests the importance of educating consumers and reconsidering the clarity of label design. Table 3 also reveals that for some products, only a small number of participants correctly identified the Nutri-Score label. Nesquik Extra Choco cocoa drink powder and Hungarian ESL fresh milk were correctly labelled by only one participant each. This supports earlier findings that the Nutri-Score labelling of these two products triggered notable emotional response. Similarly, only six participants correctly identified the Nutri-Score for Coca-Cola Light carbonated soft drink and four did so for Nestlé Chocapic cereal. In these cases, the emotion of surprise was particularly pronounced, and a significant proportion of participants misclassified the products.

Table 3. The number of fixations for each AOI and the results obtained by Random Forest (RF) analysis.

Termékek	**AOI-1**	**AOI-2**	**AOI-3**	**AOI-4**	**AOI-5**	**AOI total**	**RF (%)**	**RF val. (%)**
alpromilk	34	11	1	0	0	46	90	85
margarine	6	9	1	0	1	17	76	60
margarine2	16	13	3	1	0	33	66	85
chocapic	2	1	1	0	0	4	72	65
cocoapowder	0	0	1	0	0	1	78	75
coffee	4	1	1	0	0	6	74	75
coffee2	5	2	0	0	0	7	72	75
cola	2	1	3	0	0	6	80	75
cookie	14	10	4	0	1	29	68	60
dressing	9	10	1	0	0	20	76	70
jam	19	3	4	0	0	26	70	80
ketchup	11	9	5	0	1	26	74	75
knoppers	10	10	0	0	0	20	74	85
milk	3	7	3	1	3	17	82	95
milk2	0	0	0	1	0	1	66	80
mueslibar	7	3	1	0	0	11	72	80
rittersport	11	2	0	0	0	13	68	60
spread	7	3	3	0	0	13	64	80
vegameat	7	3	2	2	0	14	58	80
yogurt	7	5	3	0	0	15	66	65

Abbreviations: AOI: Area of Interest; 1: one Nutri-Score label viewed by the participant; 2: two Nutri-Score labels viewed by the participant; 3: three Nutri-Score labels viewed by the participant; 4: four Nutri-Score labels viewed by the participant; 5: five Nutri-Score labels viewed by the participant; RF = Random Forest decision tree.

DISCUSSION

The Nutri-Score label is a simple front-of-pack label that presents minimal information and is therefore quick to interpret. However, the question remains: can consumers truly understand this type of label? Research by Cerf et al. (2024) showed that while participants' perceptions of product quality ratings were accurate, their understanding of the Nutri-Score label was limited and confused. The study also revealed that some individuals struggled with the concept of "healthy", indicating difficulty in identify what qualifies as healthy food. Yamim and Werle (2025) investigated the effect of the discrepancy between consumers' expectations and the actual Nutri-Score label on purchase intention. Their findings showed that when a product received a better-than-expected labelling, purchase intention increased, even if the nutritional value of the product was lower (e.g. a food labelled Nutri-Score D). Conversely, a worse-than-expected label decreased purchase intention, even for products considered healthier, such as those labelled Nutri-Score B. This study also highlighted the frequent mismatch between consumer expectation and actual label classification, complicating consumers' ability to correctly identify the Nutri-Score for certain products. Castellini et al. (2024) investigated which type of front-of-pack label most effectively supports food choices, particularly when creating menus for people with special dietary needs (e.g. high cholesterol). The results indicated that Nutri-Score label did not provide sufficient information, whereas the NutrInform Battery label was considered reliable and useful by participants. These findings align with the results of the present study suggesting that the Nutri-Score label may be difficult for consumers to interpret.

CONCLUSIONS

In the present study, the Nutri-Score labelling system was evaluated using both facial analysis software and an eye-tracker. First, ANOVA was used to identify which emotions showed significant differences and subsequent data analysis focused on these emotions. Among the six basic emotions two were found to exhibit significant variation: happiness and surprise. A repeated measures analysis of variance (RMANOVA) was then conducted to explore the interaction between the 20 products in the study and these two emotions. An interesting finding was that both happiness and surprise showed the highest values for nearly the same products. The Hungarian ESL fresh milk, Coca-Cola light carbonated soft drink, Nestlé Chocapic cereal and Nesquik Extra Choco Instant cocoa drink powder all showed intense manifestations of both emotions. This may be because the sight of the correct Nutri-Score labelling or the measurement situation is embarrassing for the participants, which may manifests as laughter or smiling. Additionally, both correct and incorrect answers can trigger these emotions, and some participants may express surprise through laughter. Following the emotion analysis, choice prediction was carried out, preceded by a collection of the proportion of participants who correctly identified the Nutri-Score classification for each of the 20 products. In total, six products were identified for which participants demonstrated confidence and provided the correct answer. Choice prediction was performed using the Random Forest (RF) statistical method for the fixation duration (FD) parameter. The analysis included only the data participants who correctly identified the Nutri-Score for each product. The results indicate that there are few products for which the consumer can immediately determine its Nutri-Score classification. Alpro's sugar-free almond drink was the easiest product to classify, followed by

Venus baking margarine, for which a high percentage of participants also made correct Nutri-Score classification. In addition, the results showed that there were few products in the study for which making a judgement appeared to be particularly difficult. In none of the cases did participants view all five Nutri-Score labels before making a decision. However, for certain products, the proportion of correct responses was notably low. Surprisingly, only one participant correctly identified the Nutri-Score for Nesquik Extra Choco cocoa drink powder (rated Nutri-Score A) and Magyar ESL fresh milk (rated Nutri-Score E). Similarly, only six participants correctly classified Coca-Cola light carbonated soft drink (rated Nutri-Score B) and four correctly classified Nestlé Chocapic cereal (rated Nutri-Score A). These findings suggest that consumers possess limited knowledge and background understanding of the Nutri-Score label, making it difficult for them to determine the classification of a product. To address this issue, the label may need to be revised or redesigned, or alternatively, consumers should be educated more effectively about its meaning and application.

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