Wine label design proposals: an eye-tracking study to analyze consumers’ visual attention and preferences

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Abstract

Purpose – The main purpose of this study is to analyze how consumers’ visual attention to wine label design correlates with their preferences. Accordingly, this study uses quantitative eye-tracking metrics to understand which design proposal has greater visual salience. A more specific objective was to assess which design proposal was preferred to be marketed.

Design/methodology/approach – The experiment involved evaluating of three different labeling proposals of an Italian winery. Infrared eye-tracking was used to measure implicit eye movements on the three bottles displayed, simultaneously, on a computer screen. A generalized linear model was used to test how consumers’ visual attention to wine label design correlated with their preferences.

Findings – The design proposals were evaluated significantly differently, with one set being preferred. In general, a strong positive relationship was found between pausing to peruse a specific design proposal and making an explicit choice of the same bottle.

Research limitations/implications – The main limitation of the experiment concerns the sample interviewed. As the sample is homogeneous, the results may not be generalizable to other segments. Furthermore, the addition of electroencephalographic devices that monitor brain activity could provide crucial information for understanding consumer behavior during the purchase decision-making process.

Practical implications – Eye-tracking methods could be useful for designers and wine producers during the evaluation process of design projects.

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1. Introduction

The modern wine market is very competitive, and wine companies must understand the consumers’ needs and purchasing decision-making process to achieve the best market positioning and increase profits (Piacentini and Szmigin, 2015). A key determinant of choice is product quality, but this can only be assessed at the time of consumption (Ghidossi et al., 2012). Therefore, in the absence of tasting or prior product knowledge, brands must find innovative ways to communicate their value and quality. In this context, packaging and labels have become important elements to consider because they are the first points of contact between the product and the consumer (Galati et al., 2018). Therefore, the product must stand out on the shelf, where it competes with many other proposals, to be chosen by the consumer (Gofman et al., 2009). Leder et al. (2016) point out that consumers tend to pay attention to stimuli that they perceive as attractive during the decision-making process. Thus, label design has become an important issue and been discussed in several academic publications (Silayoi and Speece, 2007; Wells et al., 2007; Gelici-Zeko et al., 2013; Becker et al., 2011; Clement, 2007). Many scholars have demonstrated that brand perception and product quality are influenced by the visual appearance of the label (Ares et al., 2011; Orth and Malkewitz, 2008; Pantin-Sohier, 2009; Rompay and Pruyn, 2011). Based on these observations, it can be argued that label design is a key tool for companies to communicate about their brands and products and for marketers to understand consumer decision-making processes (Celhay and Remaud, 2018). Questionnaires, interviews and focus groups are the most commonly used techniques by marketers (Elliot and Barth, 2012; Celhay and Trinquecoste, 2015); however, these are not always able to provide objective results on consumer behavior regarding product choice (Ariely and Berns, 2010; Babiloni et al., 2014; Alvino et al., 2018, 2019). This is because most people are unwilling or unable to explain their purchasing decision, in fact 95% of the decision-making process occurs at an unconscious level in the case of consumer goods (Zamani et al., 2017). To overcome this limitation, the discipline of neuromarketing, which combines neuroscientific techniques, psychology and traditional marketing, has recently been developed in the wine sector to understand the unconscious processes occurring in the minds of consumers (Cruz et al., 2016). The goal of neuromarketing is to establish a solid neuropsychological theory that allows us to understand consumer behavior by combining different neuroscientific methods and techniques specialized in visual attention and cognitive research (Robaina-Calderin and Martin-Santana, 2021). One of the main techniques is eye-tracking, which studies visual behavior (e.g. fixation point, gaze and pupil dilation); visual attention mechanisms; and consumer engagement (Alvino et al., 2021).

In the literature, most research on the topic has been carried out using eye-tracking, as not only can eye fixations predict consumer preferences, but also highlight which information and design features influence purchase preferences (Motoki et al., 2021). Laeng et al. (2016) use this technique to investigate how visual attention relates to consumer preference and what information is most observed. Additionally, they test the effectiveness of real-world marketing decisions by comparing a bottle of wine chosen for marketing with
three other design alternatives that had been discarded by the producers. Merdian et al. (2020) attempt to discover how unconscious perceptions, and conscious reactions differ when evaluating wine bottles on a shelf based on the expense, by using quantitative eye-tracking metrics and interest- and value-based questions, respectively. However, only few studies in the literature that have use eye-tracking techniques to analyze the distribution of attention on the labels of wine bottles as a communication tool and, above all, as a means to evaluate different design proposals during product conception, before making marketing choices.

Therefore, the experiment proposed consists of evaluating three label design projects of a Sardinian company combining implicit data (i.e. eye movement indicators) with explicit preferences, (i.e. participants’ preferences). The research uses a paradigm and method similar to that of the above-mentioned studies, but proposes an experiment on design alternatives before putting the product on the market. The main purpose of this study is to analyze how consumers’ visual attention to wine label design correlates with their preferences, using quantitative measures of gaze. Eye-tracking method was used to collect objective data on how consumers view and process visual cues because it is a suitable technique to measure visual attention during product package analysis, reducing the limitations caused by memory effects and communication delays present in self-reported questionnaires (Rebollar et al., 2015; Monteiro et al., 2020). The specific objectives are to identify the design features that most influence consumers’ visual attention. In particular, to understand which design proposal was preferred by them to help marketers and companies choose the design of the product to be marketed.

2. Theoretical framework and research questions

2.1 Wine label design
In the wine market, notoriety is determined by label design. Producers invest in designers and marketers who use a variety of images, colors, fonts and information to entice consumers to buy the company’s products (Vollherbst and Urben, 2011). According to Thomas and Pickering (2003), the front label is more important than the back label for consumers who buy wine online and in brick-and-mortar shops. Therefore, to create a wine label, designers must make decisions regarding the visual appearance of the packaging, influence consumers’ expectations and modulate their propensity to purchase (Deliza and MacFie, 1996; Piqueras-Fiszman and Spence, 2015). Hoegg and Alba (2007) divide bottle claims into two categories: verbal and visual. The former comprises all information that characterizes and details the product, and the latter comprises images, symbols and colors that evoke specific sensations in the minds of consumers, including taste perception. According to Rebollar et al. (2017), in contrast to verbal aspects, there are still some visual aspects that need to be further studied and investigated, in particular the image displayed, material of the label, position and relationship between these signals. Images and icons are the most important semiotic signs (Peirce, 1955). In wine labels, icons, such as symbols related to terroirs, landscapes, winery and grapes, evoke images corresponding to the real world. They are of fundamental importance to enable the consumer to immediately grasp the area of origin, assess the taste of the wine and then, make a purchasing decision. Therefore, the territorial icon is a visual clue that influences purchase decisions, as it generates positive expectations in the minds of consumers by reflecting on the company and evoking the brand. Color is an essential semiotic sign in the visual design of wine labels. Kress and van Leeuwen (2020) in their color grammar model state that, in general, color can have three different functions: ideational, interpersonal and functional. When it comes to wine, ideational function is the most representative because it refers to the ability to link
visual appearance to taste. Another relevant element for attention and visual perception is label texture. For a brand manager, choosing the right front label ensures strong brand vision and differentiation from other brands. The most common choices for the front are paper or film. While the former expresses a traditional idea that evokes a classic and natural look, the latter expresses an elegant and modern look that enhances the product through transparency, creating the illusion that the label is printed directly on the bottle. Thus, the choice of texture is crucial for evoking specific sensations in consumers. Finally, the positioning of such clues affects the fluidity of processing and consumer preferences. Sundar and Noseworthy (2014) examine how brand positioning on the packaging affects capitalization, finding that there is a correspondence between logo power and height. Some studies have attempted to investigate consumers’ aesthetic preferences through all possible combinations of layouts, colors and icons using traditional questionnaires, thus relying on the explicit responses of the participants (Rocchi and Stefani, 2006; Boudreaux and Palmer, 2007; Pelet et al., 2020).

Based on the previous considerations, the research question was as follows:

*RQ1. Is there a significant difference in the visual attention in relation to the wine labeling design?*

### 2.2 Eye-tracking techniques in labeling analysis

In addition to being perceived as positive or negative, a stimulus requires a certain level of attention on the part of the consumer, thus competing in terms of attention and design (Meredian et al., 2020). Therefore, attention has become a key concept in consumer behavior literature (Engel et al., 1995; Hawkins et al., 1992; Peter and Olson, 1998; Schiffman and Kanuk, 2013). Attention is usually associated with how well consumers manage to maintain their concentration on specific stimuli within their viewing range (Solomon et al., 2002), and is measured using eye-tracking technology. Eye-tracking through specific devices, allows eye movements, gaze fixation points and pupillary changes to be monitored (Popa et al., 2015). It measures the distribution of visual attention and allows measuring the unconscious perception processes. Most studies use this technique to analyze and measure consumer preferences for food information labels (Piqueras-Fiszman et al., 2013). For example, Pieters et al. (1999) examine the role of visual attention in product choice using eye-tracking. They find that consumers under pressure dwell more on visual aspects of the packaging as compared to verbal ones, and vice versa, when high task motivation is present. Clement (2007) and Husić-Mehmedović et al. (2017) demonstrate that packaging design influences the visual attention of consumers when choosing food products at all stages of the purchasing decision-making process: from the initial stage in which visual attention is captured, to the next stage, in which critical thinking develops in the consumer’s mind and, finally, to the physical action that leads to purchase. It is well established that visual packaging elements play a crucial role in influencing consumer behavior in shops (Yu et al., 2022); but this concept only occurs when images evoke simple concepts that are easy for consumers to understand. In the case of gluten-free food products, Sielicka-Różyńska et al. (2021) find that verbal cues are observed more as compared to visual cues, but when combined, they decrease the level of consumer uncertainty. This technique is beginning to be used in the wine industry. Mokrý et al. (2016) use dwell time averaging to analyze which visual attributes of wine labels most influence the choice of Generation Z consumers, specifically focusing on price, type, premium, shape, color and label information.
Monteiro et al. (2020) focus on the role of wine awards and confirm that visual attention to wine labels influences individuals’ desires, which consequently affect individuals’ perception of wine quality.

Laeng et al. (2016) conduct experiments by using eye-tracking and pupillometry to analyze the different reactions of consumers to labels used commercially and other design projects discarded during the selection of the final product. Researchers demonstrate that gaze is a predictor of preferences, and visual cues capture the gaze of participants to a greater extent as compared to verbal cues, reaffirming the concept that design affects consumers’ buying behavior. Research shows that some designs are preferred over others on the basis of their “perceptual fluidity,” i.e. their ability to process information more easily, highlighting that cognitive load can influence users’ attention and visual behavior. (Reber et al., 1998, 2004; Winkielman et al., 2005, 2006; Milosavljevic et al., 2011; Wang et al., 2014; Laeng et al., 2016). Merdian et al. (2020) conduct a similar study using two eye-tracking indices (total duration of fixation and time to first fixation) to analyze the perceptual differences between four categories of bottles divided by price and style. The results confirmed a relationship between attention distribution and explicit statements, thus confirming the theories of previous studies. However, only few studies have used eye-tracking techniques to evaluate different design proposals during the product conception phase before placing a product on the market. Therefore, this study involves an experiment on the evaluation of three label design projects of different types of wine of a Sardinian company, combining implicit data (eye movement indicators) with explicit preferences (preferences of consumers) to provide guidelines for designers and marketing directors when designing wine bottle labels. With respect to the studies cited above, we want to not only investigate whether there are useful eye-tracking indices other than those used by Merdian et al. (2020), but also understand which sets of bottles communicate the theme of territoriality to consumers the most, without a priori discarding any design proposal, as opposed to Laeng et al. (2016). The present study analyses consumer behavior and aims to test whether there is a correspondence between visual attention and product preferences. Indicators of participants’ eye movements (implicit data) are combined with explicit evaluations to better understand consumer preferences in the context of wine bottle design and to help designers and marketing directors during wine bottle design.

Accordingly, the corresponding research questions are as follows:

RQ2. Which eye-tracking metrics describe consumer behavior during the assessment of wine bottles?

RQ3. Is there a significant correlation between preference of wine bottle and eye movements’ metrics?

3. Materials

3.1 Stimuli

The Palmalias winery produces three different types of wine: red (Cannonau), white (Vermentino) and pink. The winery proposes a new labeling model to meet the needs of today’s consumers choosing three different Sardinian icons to express the strong identity and character of the product and its history.

This message is summarized in three design proposals:

1. Sardinian folk costumes;
2. Sardinian symbols (Sa Pintadera); and
3. Wind-blown oleaster.
Each proposal comprises both visual and verbal cues. The former cover almost the entire label and are considered the most important because they are perceived by consumers the most during product selection. The design proposals are rather simple, ensuring a similar cognitive load so as not to affect consumer observation. Within each set, the chosen territorial icon is designed differently, depending on the type of wine. Images and colors vary to impart uniqueness and visibility to the brand. Such a proposition is a common choice by designers to help customers identify the winery's brand, and, create a unique identity among an array of products (Caldewey and House, 2004).

3.1.1 Sardinian folk costumes. The first proposal is dedicated to telling the story of Sardinia with the help of Sardinian folk costumes. Made of precious and colorful fabrics, costumes are symbols of different cultures and still worn today in many traditional and religious festivals. Almost every large town has its own typical costume, and there are more than 400 different models. Nevertheless, all costumes have some common features: women wear a veil, cape or shawl, whereas men wear the Sardinian beret. The labels depict two female faces and a male face in the center and are printed on FSC paper. The visual cues occupy almost the entire label and are depicted in vivid colors, both achromatic (black and white) and chromatic (red, green and blue), whereas the verbal cues (name of the wine and brand) are positioned below the images.

3.1.2 Sardinian symbols (Sa Pintadera). The second proposal aims to describe the history of the land of Sardinia where the link with symbolism remains strong. The label is inspired by Sa Pintadera, one of the most important symbols of Nuragic Sardinia. It comprises a circle, symbolizing the cyclical nature of life, seasonal cycle, rhythms of nature and thus, abundance and fertility. Sa Pintadera is certainly an emblematic object that personifies archaic Sardinia, such that it has become a symbol of representation as much as the flag of the Four Moors. This indicates a strong brand, representing prosperity that was typical of Sardinia in the past in many ways. The labels are made using the transparent screen printing technique, in which only the lines of the central symbol are colored white, with some elements painted in a bright contrasting color. Similar to the first proposal, the visual cues are predominant and the verbal information is positioned below the image.

3.1.3 Wind-blown oleaster. The third proposal shows an oleaster, a typical Sardinian plant, bent by the wind with a distant landscape in the background. The plant is screen printed, colored entirely white and develops vertically, occupying almost the entire front surface of the bottle. In this case, verbal cues are distributed both above and below the image to frame it.

Figure 1 shows the wine labels for each design proposal. For the sake of convenience, in the following text, they will refer as costumes (2a), symbols (2b) and oleaster (2c) bottles. The abbreviations are explained in the image captions.

3.2 Participants
The sample consisted of \( N = 60 \) participants (31 female and 29 male), who are master's students of the marketing course at the University of Florence. Sixty-five percent of them are aged between 25 and 39 years, and the rest are aged between 18 and 24 years. Their knowledge of the world of wine was medium to poor, while their consumption frequency varied habit was between three and four times a week (50%), once a week (30%) and once a month (20%). The participants are drinkers of all three wine types. They were chosen as marketing and communication experts. All participants received a red wine bottle from the winery, to make them more motivated and involved in the experiment.
Visual attention and preferences

Figure 1. Experiment stimuli

Notes: C = Costumes; S = Symbols; O = Olesner; R = Red wine; W = White wine; P = Pink wine
3.3 Hardware and software used
Pupil Invisible glasses, a new type of head-mounted eye tracker from Pupil Labs, are used in the experiment. They look like normal eyeglasses, but have sensors installed in them. They recorded an IR video at 200 Hz, with a resolution of 192 × 192 pixels. The device has two eye cameras, one for each eye, next to which is an IR LED to ensure good illumination of the eye, and a detachable scene camera that captures a video of the scene. The cameras record all gaze data except the pupil diameter. The glasses are connected to a companion device (android phone) with a USB-C cable, which the app automatically captures a video of the scene during a recording whenever it is connected (Tonsen et al., 2020). In our case, the device is remotely connected to the computer, on which we run the experiment. The computer monitor is a TFT-LCD with a width of 60 cm and a height of 34 cm, with a refresh rate of 60 Hz, resolution of 2,560 × 1,440 pixels, and brightness set to 100%. The experiment is built using EventIDE, which is a software created by Okazolab. This software allows the device to be connected such that the recording of eye movements begins at the start of the experiment in a synchronized manner. This software is suitable for neuroscience, behavioral research and usability testing. It allows us to create an automated procedure, setting a specific duration for each image administered and recording data on participants’ eye movements and responses.

4. Methods
4.1 Procedure and tasks
Participants who arrived at the laboratory were informed about what the test consisted of and which tasks they were going to perform. Before starting the experiment, participants were shown a presentation summarizing the company’s mission to hint at the context. Then, they filled in a questionnaire regarding preliminary information about themselves, their knowledge of wine and their consumption habits and preferences. They were sitting at a desk and wore the eye-tracking glasses. Their heads were positioned at a distance of 60 cm from the screen during all experiment with the help of a chin-rest, allowing a more accurate calibration of eye movement, performed before starting the experiment. Calibration includes looking at several marks on a screen to collect enough data to modify the parameters of an adjustable model (Villanueva et al., 2004).

As Figure 2 shows, each screen shown for 7 s and comprised three different bottles (costumes, oleaster and symbols) shown simultaneously, categorized by the type of wine (i.e. red, white and pink). The sequence of the screens and positions of the bottles was random.

We have chosen the random method to avoid influencing the research unduly, as stimuli located in the center are usually observed the most. After each screen, the participants had to express their preferences by choosing one of the three bottles they had just looked at. The choice was followed by a 3-s-long black screen to avoid fatiguing the participants (Atalay et al., 2012).

4.2 Eye-tracking metrics
Given that one aim was to analyze the visual attention of consumers, the eye movements were recorded for each stimulus. After aggregating the raw eye-tracking data into fixations and saccades, the following information was calculated for each eye fixation: fixation number; x-y coordinates in pixels; and start time, duration and end time in milliseconds. A fixation is considered a cluster of gaze coordinates within a specified range in space and time, whereas a brief peak in the velocity signal of the gaze signal may correspond to a saccade (Hessels et al., 2018). To obtain this information, the EventIDE software uses the fixation detection algorithm proposed by Engbert and Kliegl (2003) and Engbert and
Mergenthaler (2006). The algorithm was designed for microsaccades, but is equally applicable to normal saccades with an adapted velocity threshold, which, in our case, is a threshold of at 10 degrees of visual angle per second. For a more in-depth analysis of the calculation procedure used by the software, please refer to Engbert and Kliegl (2003) and Engbert and Mergenthaler (2006).

Subsequently, these elements were spatially aggregated into specific areas of interest (AOIs), which in our case are the entire bottles. This decision was taken because to understand which design proposal was preferred by consumers, it was sufficient to select the individual bottles. Furthermore, as the visual cues, such as pictorial information, were the predominant information and the ones that differed most than the verbal ones, it was not relevant to divide the AOIs into several categories. Figure 3 shows the AOIs of each bottle and is a graphical representation of the collected data showing a scanpath plot, which is an ordered set of fixation points (depicted by squares) connected by saccades (depicted by lines).

After the spatial aggregation of eye movements on AOIs, the movements can be summarized through metrics. Based on Holmqvist et al. (2011), seven metrics were used, divided into three categories: based on time, space and time-space. Table 1 shows and describes the eye-tracking metrics, wherein \( j \) represents each AOI.

4.3 Data visualization and statistical analysis

The metrics obtained were analyzed through both data visualization techniques and statistical methods.

The former consisted of heatmaps, often used in marketing to analyze the visual attention behavior of consumers. Heatmaps are standard representations composed of 2D matrices, in which each cell is assigned a color according to its value. In our case, the values were composed of the aggregation of fixations according to their duration (Drusch et al., 2014). The latter was mainly characterized by methods to build a predictive model of preference, to test how consumers’ visual attention to wine label design correlates with their preferences. For this reason, the first step was to evaluate the effect of multicollinearity among the different eye-tracking metrics. Common methods used to detect multicollinearity are based on examining correlations between pairs of predictors, however, this is limiting. It is possible for pairwise correlations to be small, but for a linear dependence to exist between three or more variables. Therefore, many regression analysts often rely on variance inflation factors (VIFs) to detect multicollinearity (Graham, 2003). The VIF is the ratio of the variance
Figure 3.
Scanpath plot and AOIs
of a parameter estimate in a model that includes several variables to the variance of a model constructed using only one variable. Thus, it provides an index that measures the extent to which the variance of the regression coefficient increases owing to multicollinearity.

Then, the VIF is computed by following equation (1):

\[
VIF = \frac{1}{1 - R_i^2} = \frac{1}{\text{Tolerance}}
\]  

(1)

where \( R_i^2 \) represents the unadjusted coefficient of determination for regressing the \( i \)th independent variable on the remaining variables. The reciprocal of the VIF is known as tolerance. Both VIF and tolerance can be used to detect multicollinearity. If \( R_i^2 \) is equal to zero, then the variance of the remaining independent variables cannot be predicted from the \( i \)th independent variable. Therefore, when the VIF or tolerance is equal to 1, the \( i \)th independent variable is not correlated to the remaining variables, which means that multicollinearity does not exist in this regression model. In this case, the variance of the \( i \)th regression coefficient is not inflated.

Generally, a VIF above 4, or tolerance below 0.25, indicates that multicollinearity might exist, and further investigation is required. When the VIF is higher than 10, or the tolerance is lower than 0.1, there is significant multicollinearity that needs to be corrected. The most commonly used method for correcting this problem is to remove highly correlated variables, as this ensures that the individual effects of the independent variables on the dependent variable can be distinguished (Mason et al., 2003).

The second step was to test and train different statistical methods using the noncollinear eye-tracking metrics to determine the method that best describes the phenomenon. The following equation (2) is used:

\[
P\{\text{Design proposals}\} = f(\text{eye - tracking metrics})
\]

(2)

where \( P\{\text{Design proposals}\} \) is the dependent variable representing the probability of participants choosing among the three design proposals, that is a function of the independent variable, i.e. eye-tracking metrics.

5. Results
The data collected comprised explicit and implicit responses. The former were the preferences expressed by the participants through their preference of wine bottles. The
latter were the participants’ eye movements recorded as fixations and saccades. The former was analyzed through descriptive statistics, the latter through methods ranging from descriptive statistics to predictive model of preference.

5.1 Explicit responses

Figure 4 shows consumer preferences. The results were analyzed according to the type of wine used.

Among the red wines, bottles depicting costumes were chosen by 60% of the participants, followed by symbols for 28% and finally oleaster for 12%. In the case of white wines, the highest preference, (65%), was for costumes, followed by symbols (23%) and oleasters (12%). As for, pink wines, 72% of participants chose symbols, followed by costumes (20%) and oleasters (8%). For both red and white wines, the most chosen design proposition was costumes, and for pink wine, it was symbols. Therefore, the costume set represents the favored design proposal for motivating consumers to make the purchase.

5.2 Implicit responses

5.2.1 Heatmaps. The first result we calculated is cumulative heatmaps (Figure 5), by aggregating the fixations of all participants it was possible to observe how visual attention was distributed over the submitted design proposals. Figure 5 shows the results for each set of bottles, wherein the warm colors (red, orange and yellow) represent the highest values and thus, the bottles that catch the participants’ attention for the longest time. In contrast, the cold colors (green, cyan and blue) represent the lowest values, and thus, the bottles that were looked at very little. The set most looked at was that of the costumes (a), having the highest values in both red and white wines, whereas for pink wine, we find a preference for symbols. The second most watched set was that symbols (b), followed by oleaster (c). Additionally, the visual cues were the most observed as compared to the other information presented on the bottle. These results, although preliminary, already confirm the consistency and correlation with the explicit responses of the participants when choosing a bottle.

5.2.2 Statistics of eye-tracking metrics. Table 2 shows the statistics of the eye-tracking metrics (mean and standard deviation), categorized by wine and label type. Among red wines the values of all metrics are highest for costumes, followed by symbols; the results
Figure 5. Heatmaps of bottles

Visual attention and preferences

CR CW CP

(a)

SR SW SP

(b)

OR OW OP

(c)

min max
were similar for white wines, whereas for pink wines, symbols have the highest values for all metrics.

5.2.3 Predictive models. The VIF was calculated using the “car” library of R software and, according to the literature, the collinear eye-tracking metrics were maximum number of consecutive fixation (MNCF) and total number of fixation (TNF), as they have VIF values greater than 4 and tolerance than 0.1. This collinearity occurred because they are both metrics that measure the number of fixations, and presumably a bottle that has many

<table>
<thead>
<tr>
<th>Wine type</th>
<th>Metrics</th>
<th>Statistics</th>
<th>Costumes (N = 60)</th>
<th>Symbols (N = 60)</th>
<th>Oleaster (N = 60)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red</td>
<td>MNFC</td>
<td>Mean</td>
<td>7.38</td>
<td>5.72</td>
<td>5.03</td>
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<tr>
<td></td>
<td></td>
<td>SD</td>
<td>3.82</td>
<td>2.46</td>
<td>2.80</td>
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<tr>
<td></td>
<td>NFCF</td>
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<tr>
<td></td>
<td></td>
<td>SD.1</td>
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<td>2.00</td>
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<tr>
<td></td>
<td>NFF</td>
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<td>0.32</td>
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<td></td>
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<td>88.64</td>
<td>87.20</td>
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<td></td>
<td>TNF</td>
<td>Mean.5</td>
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<td>3.38</td>
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<td></td>
<td>SD.6</td>
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<td>MNFC</td>
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<tr>
<td></td>
<td>NFCF</td>
<td>Mean.8</td>
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<td>0.98</td>
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<tr>
<td></td>
<td></td>
<td>SD.8</td>
<td>2.59</td>
<td>1.58</td>
<td>1.76</td>
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<td>0.32</td>
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<tr>
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<td></td>
<td>SD.9</td>
<td>0.47</td>
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<td>0.49</td>
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<tr>
<td></td>
<td>NRA</td>
<td>Mean.10</td>
<td>2.02</td>
<td>1.85</td>
<td>1.92</td>
</tr>
<tr>
<td></td>
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<td>SD.10</td>
<td>0.97</td>
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<tr>
<td></td>
<td>TFF</td>
<td>Mean.11</td>
<td>91.43</td>
<td>79.51</td>
<td>112.17</td>
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<tr>
<td></td>
<td></td>
<td>SD.11</td>
<td>84.49</td>
<td>72.61</td>
<td>120.44</td>
</tr>
<tr>
<td></td>
<td>TNF</td>
<td>Mean.12</td>
<td>10.87</td>
<td>7.68</td>
<td>7.48</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SD.12</td>
<td>5.63</td>
<td>3.98</td>
<td>5.25</td>
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<tr>
<td></td>
<td>TTF</td>
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<td>1374.87</td>
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<tr>
<td></td>
<td></td>
<td>SD.13</td>
<td>836.79</td>
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<td>628.98</td>
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<tr>
<td>Pink</td>
<td>MNFC</td>
<td>Mean.14</td>
<td>5.97</td>
<td>8.15</td>
<td>5.42</td>
</tr>
<tr>
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<td></td>
<td>SD.14</td>
<td>3.64</td>
<td>4.31</td>
<td>3.58</td>
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<tr>
<td></td>
<td>NFCF</td>
<td>Mean.15</td>
<td>0.73</td>
<td>1.47</td>
<td>1.00</td>
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<tr>
<td></td>
<td></td>
<td>SD.15</td>
<td>1.57</td>
<td>2.52</td>
<td>1.76</td>
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<tr>
<td></td>
<td>NFF</td>
<td>Mean.16</td>
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<td></td>
<td></td>
<td>SD.16</td>
<td>0.44</td>
<td>0.49</td>
<td>0.48</td>
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<tr>
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<td>NRA</td>
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<td>1.03</td>
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<tr>
<td></td>
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<td>75.60</td>
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<td>SD.18</td>
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<td>61.73</td>
<td>68.09</td>
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<tr>
<td></td>
<td>TNF</td>
<td>Mean.19</td>
<td>8.22</td>
<td>11.53</td>
<td>6.78</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SD.19</td>
<td>4.22</td>
<td>4.55</td>
<td>4.21</td>
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<tr>
<td></td>
<td>TTF</td>
<td>Mean.20</td>
<td>815.97</td>
<td>1,264.30</td>
<td>677.15</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SD.20</td>
<td>546.64</td>
<td>738.60</td>
<td>545.64</td>
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</tbody>
</table>

Table 2. Statistics of eye-tracking metrics
consecutive fixations has a high total number of fixations as well. To solve this problem, these metrics were removed. Table 3 lists the VIF values for each metric.

The following equation (3) is used to predict consumer preferences:

$$P\{C, S, O\} = f(NFCF, NFF, NRA, TFF, TTF)$$ (3)

where $$P\{C, S, O\}$$ is the dependent variable representing the probability of participants choosing among costumes (C), symbols (S) and oleaster (O), that is a function of the independent variable, i.e. eye-tracking metrics $$A f(NFCF, NFF, NRA, TFF, TTF)$$.

The procedure was carried out through using the “caret” library of R software. To avoid overfitting, 60% of the data was used for training, 20% for validation and 20% for testing. Table 4 shows the results of the methods used: Random Forest (RF), Support Vector Machine (SVM), Generalized Linear Model (GLM), and Linear Model (LM).

As GLM performed better, with a higher area under the curve (AUC) and accuracy (ACC), and a good ratio between the amount of true positive rate (TPR) and true negative rate (TNR) results, it was used for data analysis. GLM is a useful framework for comparing the effects of several variables on different continuous variables. It is an asymmetric methodology based on the hypothesis of the existence of a cause–effect relationship between one or more independent variables and the dependent variable. In its simplest form, GLM is described by the following equation (4) (Rutherford, 2011):

$$\hat{Y} = \beta_0 + \beta_1 X$$ (4)

where $$\hat{Y}$$ is the dependent variable (also known as the predicted, explanatory or response variable); $$\beta_0$$ is the intercept – always a constant (i.e. the value never changes within the model); $$\beta_1$$ is a weight or slope (also called a coefficient); $$X$$ is the variable independent.

In our case, the dependent variable is the participants’ preference, while the eye-tracking metrics are the independent variables.

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Tolerance</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>MNCF</td>
<td>0.11329743</td>
<td>8.777518</td>
</tr>
<tr>
<td>NFCF</td>
<td>0.35250225</td>
<td>2.836861</td>
</tr>
<tr>
<td>NFF</td>
<td>0.34928418</td>
<td>2.862998</td>
</tr>
<tr>
<td>NRA</td>
<td>0.29725013</td>
<td>3.364170</td>
</tr>
<tr>
<td>TFF</td>
<td>0.76442309</td>
<td>1.308176</td>
</tr>
<tr>
<td>TNF</td>
<td>0.08311768</td>
<td>12.031135</td>
</tr>
<tr>
<td>TTF</td>
<td>0.36717069</td>
<td>2.723529</td>
</tr>
</tbody>
</table>

Table 3. Variable selection using variance inflation factor (VIF)

<table>
<thead>
<tr>
<th>Model</th>
<th>ACC</th>
<th>AUC</th>
<th>TPR</th>
<th>TNR</th>
</tr>
</thead>
<tbody>
<tr>
<td>RF</td>
<td>77.78</td>
<td>83.74</td>
<td>84.74</td>
<td>64.29</td>
</tr>
<tr>
<td>SVM</td>
<td>76.74</td>
<td>84.32</td>
<td>94.21</td>
<td>43.88</td>
</tr>
<tr>
<td>GLM</td>
<td>80.56</td>
<td>84.77</td>
<td>88.95</td>
<td>61.22</td>
</tr>
<tr>
<td>LM</td>
<td>79.51</td>
<td>84.47</td>
<td>92.11</td>
<td>58.16</td>
</tr>
</tbody>
</table>

Table 4. Predictive models results
Figure 6 shows the GLM results, in particular the ROC curve for the entire database and for each type of wine.

As Table 5 shows, white wines have the highest accuracy (ACC) and AUC values, followed by the red and finally pink wines. In all three cases, the model is good, and the closer the $R^2$-Square is to 1, the better. The model explains 70%, 80% and 60% of the variability of the dependent variable in red, white and pink wines, respectively. In addition, considering the design proposals, costumes have the highest values, followed by symbols and oleaster. The results indicate which design proposal has been preferred by consumers and consequently which choice the company should make.

Table 6 lists the significance of the metrics. The Total Time of Fixation (TTF) metric is highly significant (99.9%) in all three cases. This indicates that the bottles chosen were those that were observed for the longest time. To highlight this concept, the time of first fixation is significantly negative for red wine. In addition, for white and pink wines, the Number of Returns of Attention (NRA) is significant (99%), indicating that the bottle design in this case captured and sustained attention over time.

![ROC Curve Images](figures/roc.png)

**Figure 6.** General linear model (GLM) results and ROC curve for the entire database and for each type of wine.
6. Discussion
The experiment demonstrated that there are differences between the proposed designs for the new labeling model. Comparing the explicit answers with the unconscious distribution of attention, as measured by eye-tracking metrics, can be observed that there are strong correlations. The chosen bottles were observed for much longer, and at more than one moment of observation. This means that wines with certain territorial icons capture more visual attention because they were more representative of the Sardinian culture. The results showed that the theme was more relevant than the design of each individual label; therefore, designing the set using different images did not affect consumers’ preferences and purchase intentions. Instead, the color of the wine influenced the preference, but this was an effect derived only from the color of the bottle and not the label design.

6.1 Explicit responses
The results showed that there were clear and significant perceived differences among various label design projects (RQ1). In the case of red wines, the bottles depicting costumes were preferred more as compared to the other two labels, and the symbols were perceived as more pleasant than the oleaster. In the case of the white wines, bottles depicting costumes were more appreciated, and no significant differences emerged when comparing the other two labels. Finally, for pink wines, the bottles depicting symbols were the most attractive as compared with the others. The set that the participants chose most as a territorial icon was

<table>
<thead>
<tr>
<th>Wine category</th>
<th>ACC</th>
<th>AUC</th>
<th>$R^2$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red</td>
<td>80.56</td>
<td>84.80</td>
<td>70</td>
</tr>
<tr>
<td>White</td>
<td>81.94</td>
<td>92.27</td>
<td>80</td>
</tr>
<tr>
<td>Pink</td>
<td>80.66</td>
<td>81.59</td>
<td>60</td>
</tr>
<tr>
<td>Costumes</td>
<td>92.73</td>
<td>93.33</td>
<td>80</td>
</tr>
<tr>
<td>Symbols</td>
<td>81.25</td>
<td>84.61</td>
<td>70</td>
</tr>
<tr>
<td>Oleaster</td>
<td>78.57</td>
<td>76.66</td>
<td>60</td>
</tr>
</tbody>
</table>

Table 5. General linear model (GLM) results for each type of wine and design proposals

| Wine type | Metrics | Estimate | Std. error | $\hat{z}$-value | Pr(>|\hat{z}|) |
|-----------|---------|----------|------------|-----------------|----------------|
| Red       | NFCF    | -0.2471138 | 0.2148056  | -1.150          | 0.249976       |
|           | NFF     | 0.4615107   | 0.9759022  | 0.473           | 0.636290       |
|           | NRA     | 0.4522861   | 0.3264815  | 1.385           | 0.165950       |
|           | TFF     | -0.0174581  | 0.0062243  | -2.805          | 0.005034**     |
|           | TTF     | 0.0032009   | 0.0006649  | 4.814           | 0.00000148***  |
| White     | NFCF    | 0.2032563   | 0.3363929  | 0.604           | 0.5457         |
|           | NFF     | -1.0884086  | 1.2787723  | -0.851          | 0.3947         |
|           | NRA     | 1.0497623   | 0.4134461  | 2.539           | 0.0111*        |
|           | TFF     | -0.0039853  | 0.0040124  | -0.993          | 0.3206         |
|           | TTF     | 0.0038233   | 0.0008685  | 4.402           | 0.000001071*** |
| Pink      | NFCF    | 0.142431    | 0.177031   | 0.805           | 0.42108        |
|           | NFF     | -0.818781   | 0.891038   | 0.919           | 0.35814        |
|           | NRA     | 0.978226    | 0.308762   | 3.168           | 0.00153**      |
|           | TFF     | -0.003674   | 0.003783   | -0.971          | 0.33150        |
|           | TTF     | 0.002237    | 0.000498   | 4.493           | 0.00000704***  |

Table 6. The significance of the metrics
Notes: *$p \leq 0.05$; **$p \leq 0.01$; ***$p \leq 0.001$
the costume label because it is a typical Sardinian icon that is well-recognized and evocative of the land of origin.

6.2 Implicit responses

Icons and colors played a key role in the consumer evaluation process (Gil-Pérez et al., 2019). It is evident that the effect of visual salience (e.g. icons, colors and contrast) on capturing attention in consumer choice situations leads to different perceptions of design proposals, as products that are more visually salient are looked at for longer and are more likely to be stared at first, compared to visually less salient alternatives (Navalpakkam et al., 2012; Orquin and Mueller-Loose, 2013; van der Laan et al., 2015). Visual salience is defined as the distinguishing perceptual quality by which an element in the world stands out with respect to its alternatives and, therefore immediately attracts attention. Salience depends on information regarding color, contrast, orientation and intensity relative to the surrounding space (Itti and Koch, 2000).

Icons have had a decisive impact on consumer preferences. In general, visual cues are considered typical elements of labels and their relationship with aesthetic satisfaction is linear and positive (Celhay and Trinquecoste, 2015). Consumers have been influenced by the type of territorial icon proposed by its meaning and by the moderately modern and atypical style adopted. Indeed, other studies have however confirmed that a moderate degree of novelty stimulates consumers, attracts their attention in the shopping aisles and, above all, effectively differentiates a brand from its competitors (Talke et al., 2009; Celhay and Trinquecoste, 2015).

In the case of pink wine, the color of the wine probably had a significant influence on the preference of the bottle. The intensity of the pink color plays a role in the consumer’s perception, in particularly for Millennials: the transparent screen-printed label enhances the pink of the bottle and the vivid color of the wine is associated with a higher quality as compared to the more traditional tones of red and white wines (Elliot and Barth, 2012; Iazzi et al., 2019). Lorey (2021) found that the Millennial generation prefers pink wine based on several criteria and dimensions of which one of the most important is color. This is a real generational and sociological break from traditional patterns known to previous generational groups, particularly the Baby Boomers.

The participants chose the design that best represented Sardinian territorial iconicity and was able to hold their attention the longest. The eye-tracking metrics that defined consumer behavior are TNF, TTF and MNCF (RQ2), all of which characterize the dimension of gaze persistence and proved to be directly proportional to user preferences. According to van der Laan et al. (2015), the first fixation is not sufficient to determine the probability of consumer preferences; however total fixation duration is closely related to preference formation. Furthermore, the GLM model confirms this result. Considering the correlation between preferences and metrics, TTF is highly significant in all three types of wines, followed by NRA and time of first fixation (TFF) (RQ3). Another relevant finding can be derived by comparing the variances explained by different design proposals. Costumes were the preferred labels for white and red wines (Figure 4), which have the choice patterns with the highest explained variance (80% and 70%, respectively; Table 5). In the case of pink wine, symbols were most preferred, with an explained variance of 60%. As explained, variance is an index of the correspondence between conscious preferences and unconscious eye-tracking metrics, this could indicate that, in the case of the pink wine, the sample showed some uncertainty in the preference of symbols over costumes. This hypothesis is confirmed by the descriptive statistics in Table 2, wherein the mean values of the most significant eye-tracking metrics exhibit a smaller difference between costumes and symbols.
for pink wines than for the other wines. This means that the use of eye-tracking and metrics is useful in understanding consumer preferences, and thus, provides very useful insights into design preferences.

6.3 Theoretical implications
This study offers insights into the distribution of attention, interest, liking and preferences of wine consumers during their purchasing process. The results provided insights into consumer behavior and an understanding of the criteria consumers use to choose a product. The results show that a product must be appealing and immediately visible, but it must also sustain consumer’ attention. Based on the existing literature, we confirmed that TTF and TFF are useful metrics for understanding attentional phenomena and consumer pleasure (Merdian et al., 2020). Furthermore, we confirmed that there is a strong positive relationship between visual attention and bottle preference, with visual cues, such as pictorial information, capturing the attention of consumers the most (Laeng et al., 2016). Furthermore, in contrast to Laeng et al. (2016), who tested the effectiveness of real-world marketing decisions, we tested the effectiveness of design alternatives during the design and concept phases, allowing marketers to choose the product that should be marketed. The main theoretical contribution was the implementation of eye-tracking metrics to test which visual mechanisms played determining roles in stimulus evaluation, in addition to those already used in the literature. In particular, we found that when several simultaneous stimuli are compared, consumers tend to frequently return to the stimuli that caught their attention. Thus, attention returns are additional preference-related indicators. Finally, we found that the GLM is a good model for predicting consumer preferences.

6.4 Practical implications
Both wine label designers and wine producers could benefit from such methods to improve label selection and streamline the wine label design process. Eye-tracking methods could be very useful and supportive for marketing studies on consumer preferences and decision-making. Although eye-tracking in the food and drinks sector is an already established technique for evaluating packaging/labeling and consumer preferences, its use to evaluate design proposals during the product concept phase remains relatively novel is still quite new. This method provides objective, quantitative and predictive information on consumer preferences. The results can be useful not only for researchers but also for especially to manufacturers, designers and marketing directors.

7. Conclusions
In this study, participants evaluated and expressed their preferences based solely on the visual appearance of the product. The effects on preferences, aesthetic judgments and oculomotor parameters were evoked by label design. The first objective of this research was to test how alternative labels created for the same wine could be perceived differently, capturing attention differentially. These results make it possible to suggest guidelines for designers and marketing managers during the label concept phase. Furthermore, it was possible to understand the criteria of consumer behavior when choosing a product based on not only on the basis of initial attractiveness, but also whether it is able to sustain consumers’ attention over time.
7.1 Limitations and future research
The main limitation of the experiment concerns the sample interviewed, as it is a homogeneous sample of Italian marketing students as opposed to experts in the wine sector. Therefore, the results may not be generalized to other segments (e.g. wine lovers); for this reason, future studies must broaden the panels of interviewees and see whether there are any differences between experts and nonexperts. In addition, there are inherent limitations to the execution of the experiment, as it was carried out on a monitor in the laboratory in an unnatural shopping environment and with a controlled number of products. Accordingly, future studies should carry out experiments in a real environment, with stimuli not in digital format, to avoid losing important information on the perception of the texture of the label. A further limitation concerns the cognitive load, which was not analyzed because the device used does not record pupillary data. In general, pupillometric studies confirm that pupils tend to dilate during the observation of more interesting or more appreciated stimuli (Kuchinke et al., 2009; Johnson et al., 2010). Therefore, it might be interesting to integrate pupillary change data to further confirm the relationship between eye movements and aesthetic preferences. However, measuring eye movements is not always sufficient to understand how consumers focus their attention and why labels capture their attention (Alvino et al., 2021). Some researchers argue that eye movements are a consequence of the cognitive processes taking place in consumers’ minds, so the use of electroencephalography (EEG) devices that monitor brain activity adds crucial information to understanding consumer behavior during their purchase decision-making process (Luck and Kappenman, 2011; Rayner et al., 2015; Luke et al., 2018). In conclusion, future extensions of this study could repeat the experiment using EEG devices that monitor brain activity. This will not only allow EEG metrics to be added and compared with eye-tracking metrics, but also to analyze cognitive load and most importantly provide the possibility to polarize the participants’ attention as positive or negative phenomena without having to ask them for an explicit preference.

References


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