Chem. Percept.
DOI 10.1007/s12078-009-9058-0

# The Odor of Colors: Can Wine Experts and Novices Distinguish the Odors of White, Red, and Rosé Wines?

**Jordi Ballester · Hervé Abdi · Jennifer Langlois · Dominique Peyron · Dominique Valentin**

Received: 8 July 2009 / Accepted: 1 October 2009


**Abstract** Recently, several papers have investigated color-induced olfactory biases in wine tasting. In particular, Morrot et al. (Brain and Language, 79, 309–320, 2001) reported that visual information mostly drove wine description and that odor information was relatively unimportant in wine tasting. The present paper aims to study the relationship between the color of wine and its odor through a different approach. We hypothesize that people have stable mental representations of the aroma of the three wine color categories (red, white, and rosé) and that visual information is not a necessary clue to correctly categorize wines by color. In order to explore this issue, we adopted two complementary approaches. In the first one, we presented 18 wines (six reds, six whites, and six rosés) in dark glasses to our participants who were asked to smell the wines and categorize them into three categories: "red wine," "white wine," or "rosé wine." Because we expected categorization performance to be affected by participants' expertise, we used two groups of participants corresponding to wine experts and wine novices. The second approach was designed in order to verify whether the most salient perceptual differences among samples were correlated with the output of the ternary sorting task. Using the same 18 wines, we asked a third panel composed of trained assessors to perform a wine description, a free sorting task based on wines' odor similarity, and finally, the same ternary sorting task carried out by experts and novices. We found that experts and novices were able to correctly identify red and white wines but not rosé wines. Contrary to our expectations, experts and novices performed at the same level. Trained panelists also categorized accurately white wines and red wines but not rosé wines. From a more perceptual point of view, the free sorting task yielded virtually the same result. Finally, in terms of wine description, again, a clear segmentation was obtained between white and red wines. White wines were described by yellow or orange odorant sources, while the red wines were described by dark odorant sources. In the light of our results, cognitive mechanisms potentially involved in the organization of sensory knowledge and wine categorization are also discussed.

**Keywords** Categorization · Mental Representation · Wine Color · Wine Odor

**Abbreviations**

| | |
|---|---|
| ISO | International Organization for Standardization |
| ANOVA | Analysis of variance |
| GM | Geometric mean |
| PCA | Principal components analysis |

J. Ballester · J. Langlois · D. Peyron · D. Valentin
CSG, UMR5170 CNRS, INRA, Université de Bourgogne,
15 rue Hugues Picardet,
21000 Dijon, France

J. Ballester (✉) · D. Peyron
IUVV Jules Guyot, Université de Bourgogne,
1 rue Claude Ladrey,
21078 Dijon, France
e-mail: ballester@cesg.cnrs.fr

H. Abdi
School of Behavioral and Brain Sciences, MS: Gr.4.1,
The University of Texas at Dallas,
800 West Campbell Road,
Richardson, TX 75080-3021, USA

D. Valentin
AGROSUP Dijon,
1 Esplanade Erasme,
21000 Dijon, France

Published online: 20 October 2009

## Introduction

For primates in general, and for humans in particular, vision is the predominant sense, and so, for us, vision often drives the overall perceptual experience. For taste, this predominance is so important that vision and, in particular, color can strongly influence how we perceive or even identify food and beverages (cf. Delwiche 2004 for a review). Color can also change the perceived intensity of some odors (Zellner and Kautz 1990). For example, Roth et al. (1988) showed that a change in color obtained by modifying the proportion of green and yellow in a lemon-flavored sucrose solution changed the sweetness rating of this solution. This phenomenon suggests that we tend to associate some flavors with specific colors and that the presence of a given color can create expectations, which will, in turn, alter the perception of flavor. Such cross-modal associations have been extensively reported in the literature using explicit matching (Gilbert et al. 1996) or implicit association tests (Dematte et al. 2006). Interestingly, color–odor associations seem to be the same for different occidental cultures such as North American, English, and Dutch cultures (Gilbert et al. 1996; Schifferstein and Tanudjaja 2004). These associations can also be detected with neuromaging techniques. For example, Gottfried and Dolan (2003) carried out an experiment that combined functional MRI neuroimaging techniques and an olfactory detection task. Odors were presented at the same time as either congruent (i.e., semantically related) or incongruent images. Gottfired and Dolan found that odor detection was facilitated for congruent odor–image pair associations, which, in turn, were correlated, with enhanced neural activity in anterior hippocampus and rostro-medial orbitofrontal cortex.

According to Brochet and Dubourdieu (2001), for wine, color could even be a major factor of flavor organization. These authors reached their conclusion from a lexical analysis of four corpuses of wine tasting comments. They observed that, for all corpuses, the most important separation was between terms used to describe red wines and terms used to describe white wines. Moreover, when several corpuses were pulled together, the only clustering found in the data was linked to color. Therefore, it seems that the major consensual aspect of wine aroma descriptions expresses the color of the wine. In fact, an analysis of the specific terms used to describe the wines' aromas revealed an interesting relation between the color of a wine and its description: Red wines tend to be described by terms referring to red or dark objects (e.g., red currant, violet, black current, and cherry), whereas white wines tend to be described by terms referring to yellow or clear objects (e.g., honey, lemon, hazelnut, and butter).

This organization of wines aromas along a color dimension is reminiscent of a previous work by Hughson and Boakes (2002) who concluded that wine experts organize their knowledge about wine aromas around grape varieties. Hughson and Boakes (2002) theorized that this organization is derived from perceptual learning: Through repeated exposure to wines made of different grape varieties, experts have memorized how wine features correlate with grape varieties. As a demonstration of this organization, Hughson and Boakes (2002) showed that wine experts remember better wine descriptions corresponding to actual grape varieties than to random descriptions. Novices do not show such a difference between varietal and random descriptions. One can imagine that a similar perceptual learning occurs with wines of different colors. Through repeated exposure, one would extract the correlational structure of wine aromas linked to their colors and store this structure in semantic memory. This is the correlational structure that Brochet and Dubourdieu's (2001) lexical analysis could be capturing.

In agreement with the idea that knowledge about wine could be organized along a color dimension, Morrot et al. (2001) showed that a white wine colored in red was described with a greater number of red wine odor terms than the same wine uncolored. In their experiment, Morrot et al. first presented oenology students with two glasses of Bordeaux wines, a white one (made of Semillon and Sauvignon blanc grapes) and a red one (made of Cabernet sauvignon and Merlot grapes). The tasks of the students were to establish a list of descriptors and to indicate for which of the two wines each descriptor was the most intense. The resulting descriptions corresponded to what Brochet and Dubourdieu (2001) found in their lexical analysis: Red wines were described by red or dark object terms and white wines by yellow or clear object terms. One week after the first test, the same students had to perform the same task with two "white wines:" (1) the same white wine as previously and (2) the same white wine as previously but now colored in *red*. This time, the "red-colored white wine" was described with more terms corresponding to red or dark objects than with terms corresponding to yellow or clear objects. In other words, the red-colored white wine was *perceived* as a red wine. It seems that the perception of the red color activated, in the participants' semantic memory, the knowledge linked to the aromas usually associated with red wines. This activation may have created a discrepancy between the actual olfactory information provided by the aromas and the information coming from semantic memory. Because semantic information is less ambiguous than actual information, the semantic information probably weighed more heavily in the students' decision. However, in order to sustain such an interpretation, we need first to verify that wine drinkers have indeed built an odor memory representation of the color of wine. Obviously, the mere existence of such mental representations could depend on the expertise level. Indeed, previous works have shown that as expertise increases, the organization of chemosensory knowledge changes (Solomon 1997; Ballester et al. 2008). In line with this idea, Parr et al. (2003) investigated the occurrence of color-induced olfactory bias in wine experts and in novices. The authors hypothesized that because of their knowledge-driven expectations, experts should be more prone to experience a color-induced olfactory bias than novices. The results confirmed the authors' prediction: Experts showed a certain degree of color-induced olfactory bias, while novices gave rather indiscriminate responses (possibly because of the difficulty of the task). The results of Parr et al. suggest that experts and novices differ on their respective knowledge-driven expectations about the association of colors and aromas. However, it is not clear whether experts and novices have different underlying organization of these sensory categories.

A more direct approach was used by Sauvageot and Chapon (1983) who asked participants from three expertise levels (novices, intermediate, and experts) to "guess," using smell only, the color of four red wines and four white wines (participants were blindfolded). The results showed that whatever the level of expertise considered, participants recognized the color of wines at a level higher than chance. However, the expert group gave significantly more correct answers than the intermediate and novice groups, and no significant difference was found between the performance of the participants from the intermediate and novice groups. These results suggest that experts' mental representations are better defined than novices' representations.

The present paper aims to explore the relationship between wine color and olfactory signature. Contrary to Morrot et al.'s conclusions, we hypothesize that people have stable mental representations of the aroma of the three wine color categories (red, white, and rosé) as part of a wider conceptual network and that these representations are likely to be consistently activated even without any color input. In order to test this hypothesis, we choose to use only the odor as sensory input, and so we asked panelists to categorize the samples by color categories while the wine color was actually hidden. It should be noted that color was considered not only as a piece of visual information but as the label of a wine category in which color is one feature among many others (winemaking, context of consumption, flavor properties, and so forth). Moreover, based on Sauvageot and Chapon (1983) as well as Parr et al. (2003), we also expected categorization performance to be affected by participants' expertise level. In order to test these hypotheses, we adopted two complementary approaches. In the first approach we used two groups of participants corresponding to wine experts and novices. Each panel carried out a ternary categorization task in order to check the extent to which each color category had a typical odor pattern, which could enable recognition by tasters.

The second approach consisted into asking a third panel of trained assessors to carry out three tasks: a wine description, a free sorting task, and the same ternary sorting task previously performed by experts and novices. The goal of this approach was to verify if less directed tasks such as a wine description or a free sorting task would provide the same result as the directed ternary categorization. The wine description should also show whether assessors choose attributes having the same color as the assessed wines (as suggested by Morrot et al. 2001) even when the color of the wine is not visible.

## Materials and Methods

### Participants

Three panels took part in the study: a panel of trained assessors, a panel of novices, and a panel of wine experts. The panels are fully described below.

#### *Novice Panel*

Twenty-six novice participants took part in this study (nine females and 17 males; median age, 29.5; range, 24–53). They had neither formal wine tasting experience nor knowledge about wine making and were infrequent wine drinkers.

#### *Wine Expert Panel*

Twenty-three wine experts were recruited for this study (six females and 17 males; median age, 42; range, 32–74). They met the previously exposed requirements of wine expertise (Melcher and Schooler 1996). They were mostly wine-makers and also teachers in oenology and/or wine researchers, and all of them are frequent wine drinkers.

#### *Trained Panel*

A descriptive panel of 27 people (eight females and 11 males; median age, 27; range, 24–68) also took part in this study. These panelists had been extensively trained for 8 months to 2 years (average training, 16 months). Specifically, the panelists worked on the memorization of common olfactory references for more than a hundred attributes as well as the major taste and mouth–feel sensations typically found in wine (see Campo et al. 2008). They were also trained to rate the intensity of those attributes on a five-point structured scale. These panelists were used to describing wines in dark ISO glass, as most of the training was carried out in this kind of glasses.

## Wines

Eighteen wines (six red, six white, and six rosé) were selected from a local supermarket. All wines came from different French vineyards, were from the 2005 vintage, and were considered as premium or popular premium (see Table 1).

## Procedures

### *Ternary Sorting Task*

The members of all three panels carried out this task. Participants had to smell each wine sample in the order in which the wines were presented. Then, participants were asked to sort the different samples, only by smelling them, in three groups: red, white, and rosé wines.

### *Free Sorting Task*

Only trained panelists carried out this task. As in the sorting task, participants had first to smell each of the samples in the order in which they were presented. Then, participants had to sort the samples according to their odor similarity. Participants were allowed to make as many groups as they wished and to put as many wines as they wanted in each group.

### *Description of Wines*

The description of the odor of the wines was carried out by the members of the trained panel. For each sample, participants were first asked to select at most five attributes among a list of 115 (Table 2). Then, they had to rate the intensity of the selected attributes on a five-point structured scale anchored between "very weak" (score=1) and "very strong" (score=5).

### *General Experimental Conditions*

The sessions took place in a partitioned odorless room. Ambient temperature was maintained at 20±2°C, and the room was ventilated between every session. In order to limit the "bottle effect," we endeavored to have as many tasters per session as possible. The novices and experts took part in one session in which they carried out the ternary sorting task. Trained panelists carried out all three tasks; first, they performed the sensory profile during 2 weeks (two sessions of nine wines each) and the free sorting task the week after. Until then, trained panelists had no information about the purpose of the study (i.e., that we were investigating the odor of the three color categories). No feedback was given to the participants at any moment during the experiment. They eventually performed the ternary sorting task in which we specifically ask them to sort the wines by color. The chronological separation between tasks and the use of different three-digit codes in each session were designed to make the three data sets as independent as possible.

The 18 wine samples were presented to the participants in a random order, which was different for each participant. For all tasks, samples were assessed orthonasally after a gentle swirl. Mineral water was available for participants to "rinse" their nose between two samples. Panelists were allowed to take as much time as they needed to perform the tasks.

Thirty milliliters of each wine were served at room temperature in dark ISO wine glasses covered by plastic Petri dishes. Samples were labeled by random three-digit codes, which were different for each task. The wines were poured about 20 min before each session. They were screened for major defects, and the bottles were sealed using a "vacu-vin®" vacuum pump between two servings.

# Results

## Wine Experts and Novices

### *Ternary Sorting Task*

The ternary sorting task was designed to evaluate whether the three wine color categories could be recognized only from the smell of the wines. For each panelist, an 18-×18-wine distance matrix was computed. In this matrix, a value of 1 at the intersection of a given row and column indicates that the wine represented by the row and the wine represented by the column were *not* sorted in the same group, whereas a

**Table 1** Wine samples with their codes

| Red | Code | White | Code | Rosé | Code |
|---|---|---|---|---|---|
| Chinon | R1 | Touraine | W1 | Anjou | P1 |
| Beaujolais | R2 | Bourgogne Aligoté | W2 | Macon | P2 |
| Hautes Côtes de Beaune | R3 | Bourgogne Chardonnay | W3 | Tonnerre | P3 |
| Lussac St Emilion | R4 | Entre deux Mers | W4 | Bordeaux | P4 |
| Coteaux du Languedoc | R5 | Coteaux du Languedoc | W5 | Coteaux du Languedoc | P5 |
| Côte du Rhône | R6 | Côte du Rhône | W6 | Côte du Rhône | P6 |

**Table 2** List of 115 attributes (translated from the original French used in the experiment) by odor families used for wine description

| | |
|---|---|
| Fruity | |
| White fruits | Quince–*apple*–*pear* |
| Yellow fruits | *Apricot/peach*–melon |
| Nuts | Date–dried fig–*prune* |
| Dried fruits | Almond–walnut–hazelnut |
| Tropical fruits | *Pineapple*–banana–passion fruit–lychee–mango–coconut |
| *Citrus fruits* | Bergamot–*lemon*–orange–grapefruit |
| Red fruits | Cherry–*strawberry*–raspberry–redcurrant |
| Black fruits | *Blackcurrant*–blueberry–blackberry |
| Other fruits | *Cooked fruits*–candied fruits–Muscat–kernel/bitter almond |
| Floral | Wattle–chamomile–honeysuckle–orange blossom–geranium–jasmine–lilac rose–lime blossom–violet |
| Spicy | Anise/fennel–cinnamon–clove–curry–juniper berry–ginger–laurel–nutmeg–pepper–licorice–thyme–*vanilla* |
| Plant | |
| Vegetal | Artichoke–asparagus–cabbage–celery–green bean–*bell pepper*–olive |
| Other vegetal | Hay/dried leaf–herbaceous–pine/resin–menthol/fresh |
| Undergrowth | *Mushroom*–humus/earth–moldy |
| Burnt/woody | |
| Burnt | Caramel–roasted coffee/chocolate–toast |
| *Woody* | Fresh wood–smoke |
| Animal | Leather–meat extract–musk/civet–cat pee–wet dog |
| Other | *Alcohol*–Kirsch–butter–lactic–yeast–cookie–fruit drop–honey–cider–rubber–cardboard–incense–ink–bitumen–flint–dust–sulfur–cold tobacco–sweat |

Italicized attributes had a geometric mean superior to 0.4

value of 0 indicates that these two wines were put in the same group. For each panel group, we used DISTATIS (which is a three-way extension of metric multidimensional scaling, see Abdi et al. 2005, 2007) to compute a weighted average distance matrix, which would describe best this group. This distance matrix was then transformed into a map using metric multidimensional scaling. Finally, 95% confidence ellipses around the wines' compromise positions were computed using resampling bootstrap techniques (see Abdi and Valentin 2007). When two confidence ellipses do not overlap, then the wines corresponding to the ellipses can be considered as significantly different at the $\alpha$=0.05 level (see Abdi et al. 2009, for more details).

The DISTATIS wine compromise plots are presented in Figs. 1 and 2, (experts and novices, respectively).

The DISTATIS maps from Figs. 1 and 2 show that, for both panels, white and red wines are quite well discriminated and recognized. Red clusters are more compact than white clusters: This indicates that red wines have been put together more often than the white wines. Rosé wines are more scattered, and they overlap with white wines. This suggests that rosé wines are not well recognized and are categorized either as whites, rosés, or, to a lesser extent, as reds. When we compare the DISTATIS maps and look at the raw data (Table 3), we can see also that the rosés categorized as reds are not the same for the two expertise levels. More than a third of experts categorized P6 as a red, whereas no novices did so. P2 and P3 were categorized with the white wines by both panels, whereas P5 was considered as a white wine only by the experts. Only, P4 and P1 were for the most part correctly categorized as rosé wine by both panels.

To confirm the interpretations derived from the DISTATIS plots, we quantified the participants' ability to sort the three types of wines in their expected categories (red, white, and rosé). To do so, we computed, for each type of wine and for each expertise level, the proportion of correct categorizations by averaging across participants. Differences in categorization performance as a function of expertise level and color category were studied by analysis of variance (ANOVA) in which expertise level was a between-wine variable and wine color a within-wine variable. We also included a first-order interaction term in the ANOVA model. Newman–Keuls post hoc pairwise comparisons (95%) were carried out for significant effects.

The results showed a significant effect of wine color [$F_{(2, 15)}$=51.39, $p$<0.001] but not of expertise level [$F_{(1,15)}$=2.83, $p$=0.11]. Moreover, the interaction was also not significant [$F_{(2, 15)}$=0.49, $p$=0.62]. A post hoc mean comparison for the

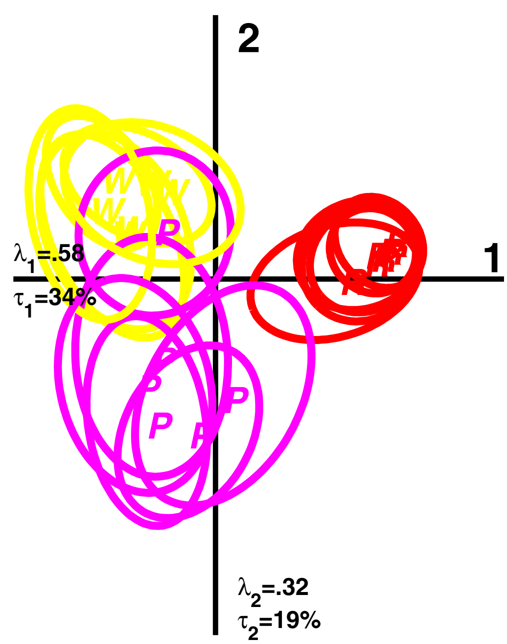


**Fig. 1** DISTATIS compromise plots from experts' ternary sorting task

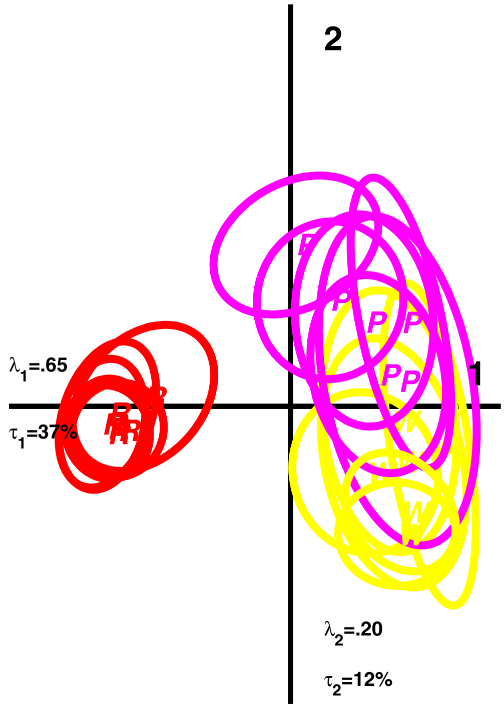


**Fig. 2** DISTATIS compromise plots from novices' ternary sorting task

**Table 3** Percentage of participants categorizing each wine in each color category computed for experts and novices

| | Experts | | | Novices | | |
|---|---|---|---|---|---|---|
| wine code | R (%) | W (%) | P (%) | R (%) | W (%) | P (%) |
| R1 | 87 | 0 | 13 | 92 | 0 | 8 |
| R2 | 57 | 17 | 26 | 63 | 13 | 25 |
| R3 | 70 | 13 | 17 | 83 | 4 | 13 |
| R4 | 91 | 4 | 4 | 83 | 4 | 13 |
| R5 | 78 | 13 | 9 | 92 | 8 | 0 |
| R6 | 74 | 0 | 26 | 92 | 4 | 4 |
| W1 | 35 | 48 | 17 | 8 | 58 | 33 |
| W2 | 13 | 74 | 13 | 25 | 54 | 25 |
| W3 | 17 | 61 | 22 | 4 | 88 | 8 |
| W4 | 22 | 52 | 26 | 13 | 67 | 21 |
| W5 | 13 | 70 | 17 | 17 | 67 | 17 |
| W6 | 22 | 52 | 26 | 8 | 54 | 38 |
| P1 | 9 | 35 | 57 | 29 | 25 | 46 |
| P2 | 23 | 41 | 36 | 13 | 54 | 33 |
| P3 | 13 | 52 | 35 | 8 | 63 | 29 |
| P4 | 13 | 30 | 57 | 17 | 17 | 65 |
| P5 | 9 | 48 | 43 | 8 | 33 | 58 |
| P6 | 35 | 26 | 39 | 0 | 58 | 42 |

*R* red, *W* white, *P* rosé

wine color effect (see Fig. 3) confirmed what we observed in the DISTATIS plots, namely, that red wines were significantly better categorized than white wines, which in turn were significantly better categorized than rosé wines.

The lack of significance of the expertise effect indicates that, contrary to our expectations (and as suggested by the DISTATIS plot), experts were not significantly better than novices at categorizing the wines into color categories by using olfactory input only.

## Trained Panelists

### *Ternary Sorting Task*

The DISTATIS plot resulting from the ternary sorting task carried out by trained panelists also showed a very good separation between white and red wines, while rosé wines are scattered in between, clearly closer to white wines than to red wines (see Fig. 4). When comparing the value of the inertia extracted by the first axis for the three DISTATIS plots (trained, experts, and novices), it is intriguing to notice that the highest value is obtained for trained participants (44%) followed by novices (37%) and finally by experts (34%). Because the discrimination between red wines and the other two categories occurs mainly along the first axis, this pattern of results suggests that trained assessors clearly identify red wines better than novices who themselves do slightly better than experts. This comparison should be interpreted with some caution, however, because trained panelists were more exposed to the wines than experts and novices.

### *Free Sorting Task*

The co-occurrence matrix obtained from the trained panelists' free sorting task was analyzed with the DISTATIS method (see Fig. 5). In the DISTATIS map, red wines are clustered together and separated from the rest of the samples. White and rosé wines are somewhat overlapping and at the same time more scattered than red wines.

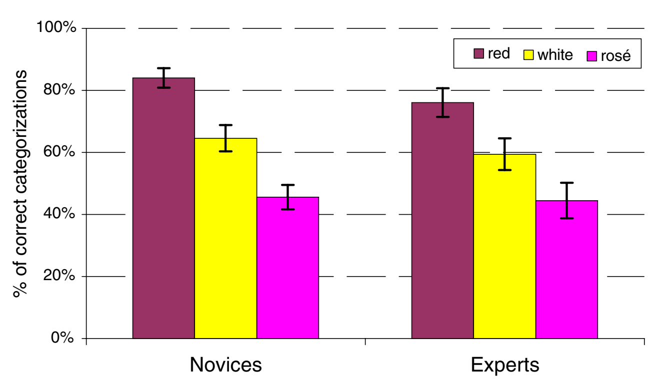


**Fig. 3** Average percentage of correct categorizations as a function of wine color and expertise level. *Error bars* represent standard errors

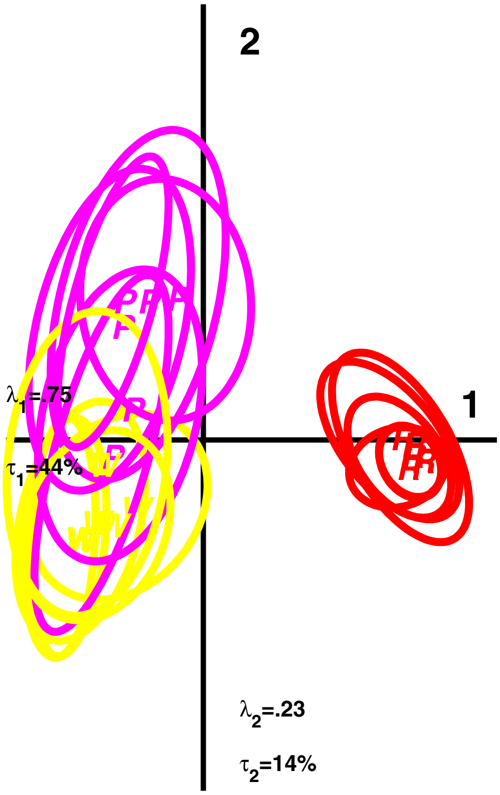


**Fig. 4** DISTATIS compromise plots from trained assessors' ternary sorting task

This suggests that red wines have some salient odor features, which are absent in white and rosé wines, while these last two types of wine seem to have some notes in common. This structure is quite close to the one obtained by the ternary sorting task in which we asked explicitly to categorize each wine in one of the three color categories.

*Description of Wines*

The intensity labels of the attributes used in the descriptive analysis were converted into intensity scores. Then, geometric means (GM) were computed for each attribute as described in Dravieks (1982). The computations were performed by cumulating, for each attribute, frequencies and intensities for all the wines. The GMs were computed as:

$$GM = \sqrt{F \times I}$$

where:

*F* frequency of citation of each attribute calculated as the number of times an attribute was cited divided by the maximum number of citations for an attribute (i.e., assessors × wines)

*I* intensity of each attribute divided by the maximal intensity for an attribute (i.e., assessors × wines × 5).

Only attributes with a GM value higher than 0.04 were selected for further analysis. Then, we computed again the GMs of the selected attributes (italicized in Table 2) for each wine. The resulting wines × attributes matrix was analyzed by principal component analysis (PCA, not shown). Hierarchical ascending classification with Ward's criterion was performed on the wines' coordinates obtained from the ten first PCA dimensions (accounting for 95.48% of the variance) in order to determine the best number of wine clusters and their composition. The resulting clusters were characterized by computing test values for each attribute (Lebart et al. 2005, p. 293). These test values are computed from the comparison, by means of a *t* test, between the mean of one variable for a given cluster and the mean of the same variable for all the classified entities. A significant positive test value indicates that the variable is significantly higher for the cluster than for the whole group of entities. Conversely, the test value is significant but negative when the variable is significantly lower for the cluster than for the entire group of observations. PCA, cluster analysis, and cluster characterization by test values were carried out using SPAD 5.5, (CISIA-CESRESTA, Montreuil, France).

The best partition of the dendogram obtained by cluster analysis yielded two clusters. The composition of these clusters as well as their characterization by means of test values are shown in Table 4. Only variables significantly characterizing the clusters are shown in this table.

Again, the cluster composition reveals a fairly good separation between reds on one side and whites and rosés

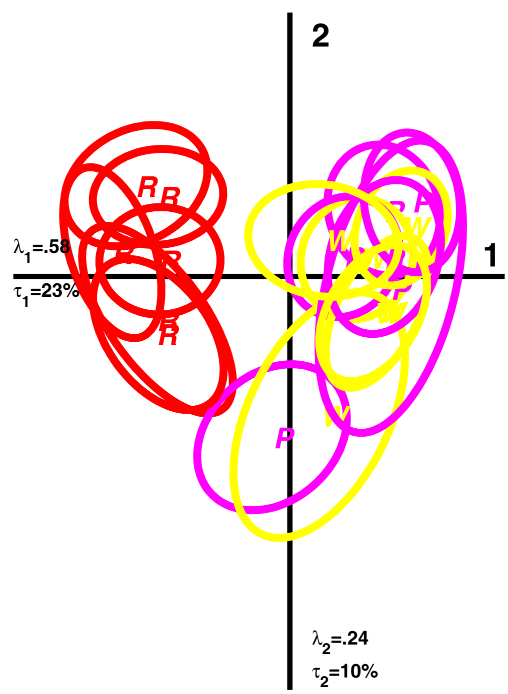


**Fig. 5** DISTATIS similarity compromise plots from trained assessors' free sorting task

**Table 4** Composition and characterization of the clusters obtained by clustering analysis on the wines' PCA coordinates

| | | Significant variables | Mean for the cluster | General mean | SD for the cluster | General SD | Test value | *p* value |
|---|---|---|---|---|---|---|---|---|
| Cluster 1 | | | | | | | | |
| P1 | P5 | Pineapple | 0.095 | 0.060 | 0.053 | 0.061 | 2.99 | 0.001 |
| P2 | *W1* | Citrus | 0.068 | 0.043 | 0.040 | 0.044 | 2.87 | 0.002 |
| P3 | *W3* | Pear | 0.113 | 0.079 | 0.063 | 0.066 | 2.64 | 0.004 |
| P6 | | Apricot/peach | 0.119 | 0.084 | 0.069 | 0.072 | 2.50 | 0.006 |
| *W2* | | | | | | | | |
| *W5* | | Blackberry | 0.027 | 0.041 | 0.017 | 0.032 | −2.34 | 0.010 |
| *W6* | | Woody | 0.023 | 0.047 | 0,.023 | 0.039 | −3.18 | 0.001 |
| Cluster 2 | | | | | | | | |
| R4 | P4 | Woody | 0.085 | 0.047 | 0.027 | 0.039 | 3.18 | 0.001 |
| R1 | | Blackberry | 0.064 | 0.041 | 0.036 | 0.032 | 2.34 | 0.010 |
| R2 | | | | | | | | |
| R3 | | Apricot/peach | 0.029 | 0.084 | 0.030 | 0.072 | −2.50 | 0.006 |
| R5 | | Pear | 0.026 | 0.079 | 0.018 | 0.066 | −2.64 | 0.004 |
| R6 | | Citrus | 0.005 | 0.043 | 0.012 | 0.044 | −2.87 | 0.002 |
| | | Pineapple | 0.005 | 0.060 | 0.012 | 0.061 | −2.99 | 0.001 |

*R* red, *W* white, *P* rosé, *SD* standard deviation

on the other side. The most salient variables characterizing cluster 1, formed by white and rosé wines, are pineapple, citrus, pear, and apricot/peach. These notes evoke odorant sources with yellow and orange colors. In contrast, cluster 2—which is mostly formed by red wines—was characterized by woody and blackberry notes, both evoking dark colored odorant sources.

## General Discussion

The present study sought to answer two questions on the nature of perceptually driven wine experts' categorizations. The first question followed previous work on the perception of wine color categories (Parr et al. 2003; Morrot et al. 2001; Sauvageot and Chapon 1983) and investigated whether participants could form color-based wine categories from smell only. The second one concerned the effect of expertise on wine categorization. As previous work showed that experts were able to categorize wine according to grape variety but that novices could not (Solomon 1997; Candelon et al. 2004; Ballester et al. 2008), we wanted to evaluate if this result would hold with a less complex categorization task such as color-based wine categorization. We expected that experts' knowledge would give them an advantage over novices and that, as a result, experts would be more accurate than novices in categorizing wines by color. Indeed, experts could use information such as varietal aromas, phenolic notes, or alcohol strength as cues to infer the color of the wine. For instance, bell pepper notes brought by methoxypyracines in some Cabernet sauvignon or Cabernet franc-based samples (as R1, R4, P4, and probably P1) can lead experts to categorize them as reds or rosés. Concerning white wines, even if we avoided including terpenol-based varieties such as Muscat, other varietal notes such as passion fruit or box tree typical of French Sauvignon blanc wines (as W1 and W4) could also have lead the experts to correctly categorize these samples.

### Are People Able to Make Color-Based Wine Categories Only by Their Smell?

Ternary sorting task results provided an affirmative answer to this question. Using olfactory information alone, all participants were clearly able to recognize red and white wines but not rosé wines. Depending on the expertise level, percentage of correct categorizations ranged between 76% and 84% for reds, 65% and 66% for whites, and 44% and 46% for rosés (correct answers average 65%). These results confirm and replicate the results we obtained in a preliminary unpublished study in which the percentage of correct answers was 74% for reds, 47% for whites, and only 37% for rosés. As we included rosé wines in our experiment, we make the task difficult especially concerning white wine categorization (because rosé wines seem closer to white wines than to red wines). This could explain why white wines had a success ratio lower than red wines. In addition, we avoided including samples too easily recognizable such as Gewurztraminer or Muscat varietals also in order to make the task more difficult. Yet, despite these rather difficult conditions, the confusion between red and white wines was very low: On average, only 7% of the red wines were misidentified as white wines and only 16% of the white wines were misidentified as red wines. Previous results for the same task (Sauvageot and Chapon 1983; Morrot et al. 2001) showed an average success rate of 70% when the choice was only between red and white wines. This value was interpreted by Morrot et al. (2001) as an indication of a poor differentiation between white and red wine flavors. However, this poor differentiation seems rather inconsistent with the fact that, according to Brochet and Dubourdieu (2001), four wine experts showed a good agreement concerning the terms that separate white wines from red wines. This inconsistency led Morrot et al. (2001) to the conclusion that "categorizing a wine as white or red without the help of the sight does not imply the identification of the odors of this wine. It rather suggests that the two tasks are very likely processed by different mechanisms (page 316)." In contradiction with this conclusion, our results show a fairly good separation between red and white wines from the explicit categorization by color, from the free categorization on a similarity basis, and even from the attributes used to describe the wines. The consistency between categorization and description points to a different conclusion than that of Morrot et al.: It is perfectly possible that categorization and description have similar mechanisms. Indeed, our results suggest that participants were able to construct a categorical representation for red wines that excluded both rosé and white wines and a categorical representation for white wines that excluded red wines.

The confusions between rosés and white or red wines could be explained by the diversity of styles of the rosé samples, which, depending on the grape varieties and the length of skin maceration, can be either closer to a red wine or to a white wine. Another explanation could be the fact that all the participants were from or lived in Burgundy where rosé wines are rarely produced and consumed. Therefore, the participants' mental representation of rosé wines is likely to be poorly defined. It is not impossible that this discrimination could be achieved by assessors from other wine regions such as Provence where rosé wines production and consumption are quite important.

Yet, the underlying mechanisms used to build those representations and make *category membership* decisions are still unclear. One possible mechanism would be based on pre-existing prototypes to which experts compare the sample to be categorized. Experts would choose the closest prototype (and the category it represents) to this sample. We could thus hypothesize that, through their wine tasting, wine tasters would derive a white and a red prototype but not a rosé prototype. This interpretation is coherent with Brochet and Dubourdieu's (2001) lexical analysis of experts' corpuses. Another mechanism would imply the comparison of the sample at hand to the closest wine exemplar stored in memory (see, e.g., Murphy 2002). Then, tasters would categorize the sample in the same category as this wine. For example, when smelling a wine in the absence of color, tasters would try to recall (consciously or unconsciously) the wine they tasted in the past that best matches the one being currently tasted. If the recalled wine happened to be red, then the taster will categorize the current wine as a red. The third mechanism, which Hughson (2003) called varietal schema theory, was previously put forward by Lawless (1985), Gawel (1997), and Solomon (1997). This mechanism involves a more analytical process and suggests that experts organize their wine-related chemosensory knowledge into a network of knowledge structures based on varietal wines and linked to a series of features (or attributes). Such a knowledge network would direct the search for relevant descriptors. In other words, experts first identify the grape variety from which a wine has been made, and then they search for the features, which they know are typically linked to this varietal wine. This process, akin to Collins and Quillian's (1969) spreading activation model, could also explain how our participants categorized the samples in wine color categories. Indeed, participants could have perceived the more salient odors of a given sample. These odors, in turn, would activate some concepts to which they are linked (in our case a wine color concept). The activation of the wine color concept would then drive the search for more relevant attributes, which, in our case, would confirm the membership to the wine color category.

So far, there is no evidence in favor of one particular mechanism rather than another, and further research is needed in this direction.

According to Morrot et al. (2001), color segmentation of the wines is mostly based on vision, but the results of the present study suggest that an olfactory-based process might also play a non-negligible role. It may very well be that both visual and olfactory information are processed in parallel to form wine mental representations but that, when both sources of information are present simultaneously, visual information dominates chemosensory information (Pangborn et al. 1963; Parr et al. 2003). In line with this observation, Lelièvre et al. (2009) showed that trained as well as untrained assessors categorized beers by color when color was accessible and by brewery when color was hidden. Lelièvre et al. suggest two hypotheses to explain their results. The first hypothesis implies that assessors—being unable to process visual and chemosensory inputs simultaneously—turn off smell and taste information and therefore rely only on vision in order to categorize beers. The second hypothesis is based on congruence seeking. Because visual information comes first, chemosensory perception is directed by color. That is, when attending to chemosensory information, assessors will, unconsciously, seek a confirmation of visual information rather than analyzing chemosensory properties of the beers. In our case, the fact that we found a clear separation between red and white wines even in the free sorting task suggests that olfactory information is also important in color-based categorical representation of wines. Indeed, if this were not the case, in the absence of color priming, participants would have used different criteria to sort the wines. In other words, our results were probably driven by immediate perceptual experience, whereas that of Morrot et al. were driven by higher knowledge structures.

### Is There an Effect of Expertise Level on Color-Based Wine Categorization?

As previous literature on wine-related categorization showed an effect of expertise on wine categorization (Sauvageot and Chapon 1983; Solomon 1997; Ballester et al. 2008), we expected to find an expertise effect with our experiment. Surprisingly, our results showed a lack of difference between experts and novices. Manifestly, top–down information concerning varietal notes or wine styles that wine experts could have brought to the categorization task could not help in this case. The simplicity of the categorization by color could explain the similar performance between experts and novices. Indeed, contrary to grape variety or winemaking processes (which are not systematically indicated in the label), color is probably the more salient information for which novice consumers systematically receive a feedback. Because of this, it is possible that, even in the case of low consumption frequencies, novice consumers are able to extract odor regularities for each color category and somehow build categorical representations of the odor of red and white wines. Equivalence between the performance of experts and novices could be also explained by the dominance of bottom–up information in the categorization process. Indeed, because previous studies have shown that experts and novices do not differ (or very little) in their perceptual skills, it is not surprising that novices and experts perform at a comparable level for a categorization task, which presumably does not involve high cognitive processing. This interpretation is supported by the results obtained by the trained panelists. Indeed, the three tasks yielded the same wine configuration despite the fact that the tasks involved different levels of perceptual and cognitive processes (verbal description, perceptual similarity, and conceptual categorization). This suggests that white and red wine color categories have very salient odor features, which enable recognition and hence accurate categorization whatever the level of expertise considered.

We have also noted that trained panelist seemed better than experts and novices at categorizing the samples in color categories. Two plausible explanations can be put forward. First, the trained panelists' superiority might be due to their higher exposition to the 18 wines of the study. Indeed prior to the ternary sorting task, trained assessors were exposed twice to the wines: once for the odor description task and once for the free sorting task. Yet, because trained panelists received no feedback on the nature of the wines during those previous tasks and because a delay of 7 days occurred between these tasks and the ternary sorting task, this explanation might not be the only one. A second explanation could be that wine experts and, even more, novices are not used to taste wine in dark glasses, and this could have disoriented them. Moreover, experts probably tend to use a holistic approach when tasting wines (i.e., different sensory modalities are processed together). In contrast, trained panelists carried out most of their training in dark glasses and were also trained to use an analytical approach. Because trained panelists systematically received verbal feedback concerning the nature of the wines they taste during their training, it is possible that, contrary to experts or novices, trained panelists processed visual and olfactory information separately and consequently stored separate olfactory and visual representations for each type of wine. However, so far, little knowledge exists in the literature, and further work is needed to fully understand the effect of different forms of sensory expertise in the construction of mental representation of sensory categories and also in the way in which sensory knowledge is organized in memory.

## Conclusion

This study showed that, contrary to Morrot and coworkers' conclusions, odor representations of red and white wines exist independently of a visual activation. We have also shown that these mental representations are stable through different expertise levels. Previous studies have shown that grape variety was an important framework according to which wine experts organize their knowledge (Solomon 1997; Hughson and Boakes 2002; Ballester et al. 2008) Taken together; these results support the idea that wine color is a major dimension of the organization of wine-related odor categories. This idea is somehow in agreement with Brochet and Dubourdieu (2001). Because white grape varieties always yield white wines but red grapes can yield red and rosé wines, it would be tempting to imagine wine knowledge organized according to a hierarchical framework in which grape varieties would be subordinate to wine color, which could play the role of Rosch's basic level (Rosch et al. 1976). The current results could also be interpreted in the more general framework of models of categorization (see, e.g., Ashby 1992; Nosofsky 1992), but our design cannot, unfortunately, dissociate between the predictions of the current two important models which assumes either exemplar based (e.g., Nosofsky 1992) or rule based (e. g., Ashby 1992) mechanisms.

## References


Abdi H, Valentin D (2007) Some new and easy ways to describe, compare, and evaluate products and assessors. In: Valentin D, Nguyen DZ, Pelletier L (eds) New trends in sensory evaluation of food and non-food products. Vietnam National University, Ho Chi Minh, pp 5–18

Abdi H, Valentin D, O'Toole AJ, Edelman B (2005) DISTATIS: the analysis of multiple distance matrices. Proceedings of the IEEE Computer Society: International Conference on Computer Vision and Pattern Recognition, San Diego, CA, USA, pp. 42–47

Abdi H, Valentin D, Chollet S, Chrea C (2007) Analyzing assessors and products in sorting tasks: DISTATIS, theory and applications. Food Qual Prefer 18:627–640

Abdi H, Dunlop JP, Williams LJ (2009) How to compute reliability estimates and display confidence and tolerance intervals for pattern classifiers using the bootstrap and 3-way multidimensional scaling (DISTATIS). NeuroImage 45:89–95

Ashby FG (1992) Multidimensional models of categorization. In: Ashby FG (ed) Multidimensional models of perception and cognition. Erlbaum, Hillsdale, pp 449–483

Ballester J, Patris B, Symoneaux R, Valentin D (2008) Conceptual vs perceptual wine spaces: does expertise matter? Food Qual Prefer 19:267–276

Brochet F, Dubourdieu D (2001) Wine descriptive language supports cognitive specificity of chemical senses. Brain Lang 77:187–196

Campo E, Do BV, Ferreira V, Valentin D (2008) Aroma properties of young Spanish monovarietal white wines: a study using sorting task, list of terms and frequency of citation. Australian Journal of Grape and Wine Research 14:104–115

Candelon M, Ballester J, Uscida N, Blanquet J, Le Fur Y (2004) Sensory methodology developed for the investigation of Sciaccarello wine concept. Journal International des Sciences de la Vigne et du Vin 38:147–154

Collins AM, Quillian MR (1969) Retrieval time from semantic memory. J Learn Verbal Behav 8:240–247

Delwiche J (2004) The impact of perceptual interactions on perceived flavour. Food Qual Prefer 15:137–146

Dematte ML, Sanabria D, Spence C (2006) Crossmodal associations and interactions between odors and colors. Chem Senses 31:531–538

Dravieks A (1982) Odor quality: semantically generated multidimensional profiles are stable. Science 218:799–801

Gawel R (1997) The use of language by trained and untrained experienced wine tasters. J Sens Stud 12:267–284

Gilbert AN, Martin R, Kemp SE (1996) Cross-modal correspondence between vision and olfaction: the color of smells. Am J Psychol 109:335–351

Gottfried JA, Dolan RJ (2003) The nose smells what the eye sees: crossmodal visual facilitation of human olfactory perception. Neuron 39:375–386

Hughson AL (2003) Cork and talk: the cognitive and perceptual bases of wine expertise. Dissertation, University of Sydney, Sydney

Hughson AL, Boakes RA (2002) The knowing nose: the role of knowledge in wine expertise. Food Qual Prefer 13:463–472

Lawless HT (1985) Psychological perspectives on winetasting and recognition of volatile flavours. In: Birch GG (ed) Alcoholic beverages. Elsevier Applied Science, London, pp 97–113

Lebart L, Piron M, Morineau A (2005) Statistique exploratoire multidimensionnelle. Dunod, Paris

Lelièvre M, Chollet S, Abdi H, Valentin D (2009) Beer trained and untrained assessors rely more on vision than on taste when they categorize beers. Chemosensory Perception 2:143–153

Melcher J, Schooler J (1996) The misremembrance of wines past: verbal and perceptual expertise differentially mediate verbal overshadowing of taste memory. J Memory Lang 35:231–245

Morrot G, Brochet F, Dubourdieu D (2001) The color of odors. Brain Lang 79:309–320

Murphy G (2002) The big book of concepts. MIT press, Cambridge

Nosofsky RM (1992) Exemplar-based approach to relating categorization, identification, and recognition. In: Ashby FG (ed) Multidimensional models of perception and cognition. Erlbaum, Hillsdale, pp 363–394

Pangborn RM, Berg HW, Hansen B (1963) The influence of color on discrimination of sweetness in dry table-wine. Am J Psychol 76:492–495

Parr WV, Geoffrey White K, Heatherbell DA (2003) The nose knows: influence of colour on perception of wine aroma. J Wine Res 2003:79–101

Rosch E, Mervis CB, Gray W, Johnson D, Boyes-Braem P (1976) Basic objects in natural categories. Cogn Psychol 8:382–439

Roth HA, Radle L, Gifford SR, Clydesdale FM (1988) Psychophysical relationships between perceived sweetness and color in lemon and lime flavored beverages. J Food Sci 53(1116–1119):1162

Sauvageot F, Chapon M (1983) La couleur d'un vin (blanc ou rouge) peut-elle être identifiée sans l'aide de l'oeil? Les Cahiers de l'ENSBANA 4:107–115

Schifferstein HNG, Tanudjaja I (2004) Visualising fragrances through colours: the mediating role of emotions. Perception 33:1249–1266

Solomon GEA (1997) Conceptual change and wine expertise. J Learn Sci 6:41–60

Zellner DA, Kautz MA (1990) Color affects perceived odor intensity. J Exp Psychol Hum Percept Perform 16:391–397