

# Becoming a beer expert: Is simple exposure with feedback sufficient to learn beer categories?



Maud Lelièvre-Desmas<sup>a,\*</sup>, Sylvie Chollet<sup>a</sup>, Hervé Abdi<sup>c</sup>, Dominique Valentin<sup>b</sup>

<sup>a</sup> ISA Lille, Charles Viollette Research Institute, 59046 Lille Cedex, France

<sup>b</sup> UMR CSG 5170 CNRS, Inra, Université de Bourgogne, 21000 Dijon, France

<sup>c</sup> The University of Texas at Dallas, Richardson, TX 75083-0688, United States

## ARTICLE INFO

### Article history:

Received 31 July 2013

Received in revised form 9 July 2015

Accepted 8 August 2015

Available online xxxx

### Keywords:

Categorization

Perceptual learning

Exposure

Expertise

Beer

## ABSTRACT

Category learning is an important aspect of expertise development which had been little studied in the chemosensory field. The wine literature suggests that through repeated exposure to wines, sensory information is stored by experts as prototypes. The goal of this study was to further explore this issue using beers. We tested the ability of beer consumers to correctly categorize beers from two different categories (top- and bottom-fermented beers) before and after repeated exposure with feedback to beers from these categories. We found that participants learned to identify the category membership of beers to which they have been exposed but were unable to generalize their learning to other beers. A retrospective verbal protocol questionnaire administered at the end of the experiment indicates that contrary to what was suggested in the wine literature, prototype extraction is probably not the only mechanism implicated in category learning of foods and beverages. Exemplar-similarity and feature-frequency models might provide a better account of the course of learning of the categorization task studied.

© 2015 Elsevier B.V. All rights reserved.

## 1. Introduction

Understanding experts' abilities is crucial for theoretical reasons but also for practical reasons such as developing efficient training programs. Among the experts' abilities, categorization is one of the most studied cognitive processes probably because it is the basis for so many other cognitive processes (e.g., recognition, identification, understanding, reasoning, and problem solving) and also because it is sensitive to the level of expertise (see, e.g., Ballester, Patris, Symoneaux, and Valentin (2008); Chase and Simon (1973); Chatard-Pannetier, Brauer, Chambres, and Niedenthal (2002); Chi, Feltovich, and Glaser (1981); Honeck, Firment, and Case (1987); Lynch, Coley, and Medin (2000); Shafto and Coley (2003); Solomon (1997); Tanaka and Taylor (1991)). So understanding how experts learn categories is critical for understanding expertise development.

Experts have been repeatedly exposed to stimuli from their domain of expertise and, from these repeated exposures, have learned to extract stimulus regularities. This idea was suggested in face processing by Dukes and Bevan (1967), (see, also, Posamentier and Abdi (2003)) who theorized that repeated exposures to different views of unfamiliar faces may help human observers extract the invariant face information. This type of learning is considered to reflect “perceptual learning,” a term defined by Gibson (1969, p.3) as “an increase in the ability to

extract information from the environment, as a result of experience and practice with stimulation coming from it.” Language theorists prefer the expression “statistical learning” (a term coined by Saffran, Aslin, and Newport (1996)) to refer to the process of learning statistical regularities. According to Kellman and Garrigan (2009), perceptual learning is “one of the most, possibly the most, important component of human expertise” and would “serve in the development of expertise in multiple ways.” One of these ways is to enable people to build categories of stimuli from the detected regularities of the stimuli they repeatedly encounter. During category learning, the observer pays more and more attention to stimulus aspects that are relevant for categorization and in contrast gradually pay less attention to irrelevant dimensions (Goldstone, 1998; Nosofsky, 1988). For example, in 1920, Hull trained human participants to learn to categorize deformed Chinese characters into categories. Each of the 12 categories was composed of exemplars that shared some invariant structural properties. For six exemplars of each category, participants were trained to associate the same arbitrary name corresponding to the category of these exemplars. Participants were then tested on six new exemplars and were able to accurately categorize these novel instances. This early experiment illustrates the importance of perceptual learning in category learning as a mechanism that extracts invariants from exemplars. Since this early work, perceptual and statistical learning have been well documented especially in the visual (Fiser & Aslin, 2001; Lu, Hua, Huang, Zhou, & Doshier, 2011), auditory (Saffran, Johnson, Aslin, & Newport, 1999; Wright & Zhang, 2009) and, to a lesser extent, tactile (Conway & Christiansen, 2005) domains.

\* Corresponding author at: ISA Lille, 48 Boulevard Vauban, 59046 Lille Cedex, France.  
E-mail address: [maud.desmas@isa-lille.fr](mailto:maud.desmas@isa-lille.fr) (M. Lelièvre-Desmas).

However, very few studies have dealt with chemosensory modalities such as olfaction and taste, even though repeated exposures to complex odorant molecules are an essential aspect of the expertise of, for example, perfumers, oenologists, and brewers. Understanding expertise in the chemical senses is a recent field of research and it has important implications for training experts because how these experts categorize their perceptions determines their abilities (Ballester, Dacremont, Le Fur, & Etiévant, 2005; Ballester et al., 2008; Hughson, 2003; Hughson & Boakes, 2002; Solomon, 1997). For example, wine experts categorize wines according to grape variety but novices do not (Ballester et al., 2008; Candelon, Ballester, Uscida, Blanquet, & Le Fur, 2004; Solomon, 1997). This effect could be explained by statistical learning: Through repeated exposures to wines from different colors or different grape varieties, wine professionals would extract the correlational structure of wine aromas linked to their colors or their grape varieties and so would develop categorical representations based on these characteristics (Ballester et al., 2008; Brochet & Dubourdieu, 2001; Gawel, 1997; Hughson, 2003; Parr, Valentin, Green, & Dacremont, 2010; Solomon, 1997).

These mental representations are often described as “prototypes” or central tendencies, as put forward by Parr, Green, White, and Sherlock (2007, p.859): “The positive association between typicality rating and wine quality [...] suggests that New Zealand wine professionals do indeed have a prototypical or ideal Sauvignon Blanc wine in mind, and that this prototype closely matches what wine professionals consider when they use the term ‘good varietal definition’.” Prototype models (Posner & Keele, 1968; Reed, 1972) assume that people abstract a central representation (prototype) from the presented exemplars of a category. Then categorization judgments about exemplars are based on distances computed between the prototype and the exemplars. But, contrary to previous studies on language acquisition or face or shape processing, these studies on wine did not provide evidence for prototype extraction and some alternative explanations could be entertained.

The feature-frequency theory (Kellogg, 1981; Neumann, 1974; Reed, 1972) proposes other close models based on abstracted information. These models assume that people register how often features or combinations of features occur among instances of a category and then base their categorization judgment on these frequency measures.

From abstracted information, experts could also have built some explicit rules about the characteristics of products (Rouder & Ratcliff, 2006; Smith & Sloman, 1994) and apply these rules to decide whether a product belongs to a category by selecting out some specific features and determining whether the product satisfies a rule suggested by these features.

Another possible mechanism could be stated in term of exemplar memorization. During their training, experts would memorize all the individual exemplars they encounter (Medin & Shaffer, 1978; Nosofsky, 1988). All these theories have been previously largely compared in different reviews of the literature (e.g. Ashby & Maddox, 2005; Goldstone & Kersten, 2003).

To sum up, it seems clear that exposure and statistical learning play an important role in the way experts in the chemosensory domain categorize their perceptions. Authors working on wine have observed category-specific changes in professionals (compared to novices) and interpreted their results in terms of learning statistical regularities and wine prototype construction. But these interpretations are quite restrictive and some alternative learning mechanisms could explain the observed results.

In the present study, rather than testing recognized experts whose training protocols are unknown, we used non-expert participants namely people who had not previously participated in formal tastings, and had no previous technical knowledge about beers (e.g., brewery visits or exposure to specialized literature)—and repeatedly exposed with feedback these participants to beers from two different categories (top and bottom fermented beers). At the end of each exposition session, participants were provided feedback about the category of each beer. We then tested if

these participants were able 1) to learn the beer categories and 2) to generalize their learning to other non-learned beers.

In order to evaluate if alternative mechanisms to prototypes could occur during this category learning, participants were also asked to fill out a retrospective verbal protocol questionnaire.

## 2. Material and methods

### 2.1. Assessors

Participants were nineteen students (6 women and 13 men, mean age: 21.5,  $SD = 1.0$  years) from the ISA-Lille (“Institut Supérieur d’Agriculture de Lille”). The experiment took place as part of a 70-hour-long course on the discovery of various occupations related to brewing. During this course, students were introduced to various technical and sensory aspects of beer. At the beginning of the study, students only knew the technical definition of the studied beers (given in the next paragraph).

### 2.2. Discussion on stimuli selection

One critical point when studying categorization and category learning is the choice of the stimuli because it is necessary to present unfamiliar categories to participants and observe their behavior during the learning period. To ensure that the participants are unfamiliar with the categories, one option is to create new, arbitrary categories of objects, but these categories may not be ecologically valid (Ashby & Maddox, 2005; Close, Hahn, Hodgetts, & Pothos, 2010). To use new, but ecologically valid categories, we chose real ill-defined chemosensory categories unknown to naïve beer consumers: the fermentation beer categories (a technical feature when brewing beers). In this framework, a beer can be categorized as a top-fermented, bottom-fermented, or a spontaneous-fermented beer, depending on the yeast used for the fermentation step. Top-fermented beers are fermented with yeasts called *Saccharomyces cerevisiae* at temperatures of between 15 °C and 25 °C. These yeasts rise to the surface of the vat at the end of the fermentation, hence the name “top.” Bottom-fermented beers are fermented with yeasts called *Saccharomyces carlsbergensis* or *pastorianus* at a temperature of between 5 °C and 10 °C. The yeasts migrate to the bottom of the vat, hence the name “bottom fermentation.” Spontaneous fermentation is an ancestral method hardly used except for the production of specific beers (e.g., lambic, gueuze, kriek). The beer sensory characteristics depend largely on the type of fermentation. Most of the bottom-fermented beers are blond, not very alcoholic, and not very aromatic. Among top-fermented beers, we find blond, amber, and dark beers that are more alcoholic, more aromatic, and often perceived as more “dense.” But these general sensory characteristics cannot be applied to all the beers of each category because of the large within category sensory variability of these beers and because there are several counter examples of beers from one category having characteristics of the other category. We call these counter-example beers: “trap beers.”

### 2.3. Stimuli

Thirty-six beers (18 top-fermented “TF” beers and 18 bottom-fermented “BF” beers) were evaluated (Table 1). The TF and BF beers were chosen so as to best represent the beer market in terms of color and alcohol content but one “trap beer” was inserted into each category. For TF beers, the trap beer was “Hoegaarden”—a wheat beer that shares more sensory properties with BF than with TF beers (low degree of alcohol, light blond color). For BF beers, the trap beer was “Bière du Démon” whose high alcohol degree (12% vol.) makes it more similar to TF than to BF beers.

A quantity of 25 ml of each beer was presented in three-digit coded white plastic tumblers and served at 10 °C with a white light. This

**Table 1**  
The 36 beers used in this experiment.

Fermentation	Beer	Color	Degree of alcohol (% vol.)	Learning	
Bottom fermentation	33 Export	Blond	4.5	Learned	
	Bavaria 8,6	Blond	7.9	Learned	
	Carlsberg	Blond	5.0	Learned	
	Heineken	Blond	5.0	Learned	
	Pelforth	Dark	6.5	Learned	
	Atlas	Blond	7.2	Non-learned	
	Bière du démon ( <i>trap</i> )	Blond	12.0	Non-learned	
	Chti	Dark	6.4	Non-learned	
	Stella Artois	Blond	5.2	Non-learned	
	Wel Scotch	Amber	6.2	Non-learned	
	1664	Blond	5.5	New	
	9X Extra Strong	Blond	8.4	New	
	Beck's	Blond	5.0	New	
	Fisher	Blond	6.0	New	
	Gold	Blond	6.4	New	
	Kronenbourg	Blond	4.2	New	
	Lutèce	Blond	6.4	New	
	Saint Omer	Blond	5.0	New	
	Top fermentation	Chimay rouge	Dark	7.0	Learned
		Grain d'Orge	Blond	8.0	Learned
Grimbergen		Blond	6.7	Learned	
Kwak		Amber	8.0	Learned	
Leffe brune		Dark	6.5	Learned	
Duvel		Blond	8.5	Non-learned	
Hoegaarden ( <i>trap</i> )		Blanche	4.9	Non-learned	
Jenlain		Amber	7.5	Non-learned	
Palm Spéciale		Amber	5.4	Non-learned	
Saint Landelin		Blond	6.5	Non-learned	
3 monts		Blond	8.5	New	
Atrébate		Dark	7.0	New	
Belzebuth		Blond	13.0	New	
Blanche de Bruges		Blanche	4.8	New	
Leffe blond		Blond	6.6	New	
Maredsous		Blond	6.0	New	
Secret des Moines	Blond	6.6	New		
Septante 5	Amber	7.5	New		

quantity was chosen in order to have a volume sufficient to evaluate correctly both the smell and the color of the beer. Participants were informed at the beginning of each session of the number of beers they will have to taste and were advised not to drink up all the samples. They could spit out the tasted beer if they wanted but none of them did. We estimated that, on average, participants drank half of each beer, which amounts to about 250–300 ml in total during one session.

#### 2.4. Procedure

The study comprised ten 40-minute sessions organized in three steps: the first step was a test denoted by  $T_0$  (Session 1), the second step was a series of exposures (Sessions 2 to 9) and the third and final

step was again a test denoted  $T_{\text{final}}$  (Session 10), identical to the first stage  $T_0$  (see schematic in Fig. 1). Sessions were spaced one week apart.

##### 2.4.1. Session 1 ( $T_0$ )

Participants were first informed that they would participate in a research study about sensory evaluation on top- and bottom-fermented beers (no information was given concerning the study objectives or the kind of beers they would taste). Then the experimenter gave the instructions to the participants. Each participant was provided with the first beer, and was asked to smell and taste it and to decide if this beer was a TF or a BF beer. Participants also had to indicate how sure they were of their choice by giving a confidence score on a three-point rating scale (not sure/sure/very sure). After the participant rated the first beer, the beer and the answer sheet were removed and the participant received the second beer with the second answer sheet, and so on for the 20 beers to be tasted. The interval between two beers was about 2 min.

Among the 20 beers, 10 were TF beers and 10 were BF beers, and among each set of ten beers, five were presented again during the exposure stage (these beers will be called “learned beers”) and five were not presented during the exposure stage (these beers will be called “non-learned beers,” see Fig. 1). The presentation order of the beers was different for each participant and determined by a William's Latin square. Mineral water and bread were available for participants to rinse between samples.

At the end of the session, the experimenter told the participants the name and the fermentation type (top or bottom) of each beer they had just tasted. The experimenter also showed the beer bottles to the participants. When participants asked the experimenter what were the sensory differences between TF and BF beers, the answer was that a sensory definition could not be given and that participants had to find their own sensory definitions.

##### 2.4.2. Exposure sessions (Sessions 2 to 9)

The eight exposure sessions were all set up in the same way. Participants were repeatedly exposed to beers from the two categories (top and bottom fermentation) and given a feedback on the category of each beer. At each session (except Session 9, see below), participants were presented with six beers, one by one, with an interval of about six minutes between beers. Among these six beers there were always three TF and three BF beers and among each set of three beers, two were *learned* beers and one was a *new* beer (not presented at  $T_0$ ). During Session 9, participants received only four beers to taste: two TF beers and two BF beers (one *learned* beer and one *new* beer for each category). So during the eight exposure sessions, each *learned* beer was tasted three times and each *new* beer was tasted once.

In each session, participants had to smell and to taste each of the six beers and to decide whether it was a TF or a BF beer. Participants also had to indicate how sure they were of their choice by giving a confidence score on a three-point rating scale (not sure/sure/very sure).

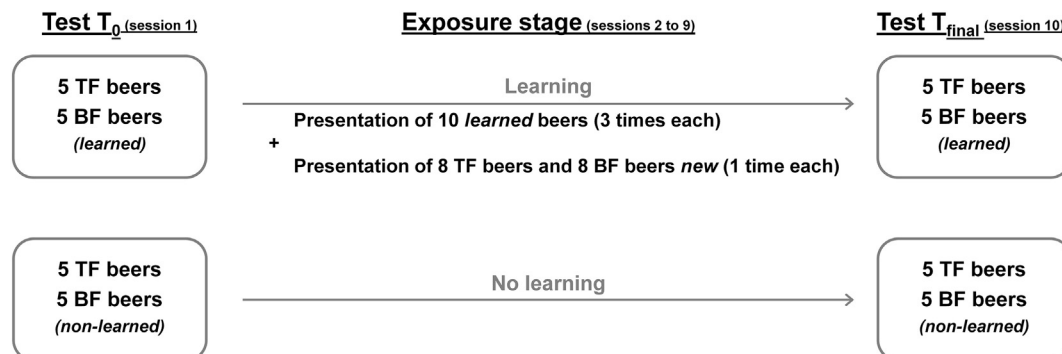


Fig. 1. Schema of the procedure.

Finally, participants had to describe the sensory characteristics of each beer using their own words. At the end of each session, a global debriefing was performed. The experimenter presented the six beer bottles and gave the correct answer (FH or FB for each beer). She also asked the participants what they thought about the beers (i.e., their sensory descriptions). Participants were free to discuss the strategies they had elaborated about for deciding the category but were not provided information by the experimenter. During this debriefing phase, participants could taste again the beers if they wanted to do so.

Mineral water and bread were available for participants to rinse between samples. The presentation order was the same for all the participants.

#### 2.4.3. Session 10 ( $T_{final}$ )

The last session was exactly the same as the first one. After they had finished tasting, participants received a questionnaire with four questions about the experiment. The objective of this questionnaire was to gain insights into the strategies used by the participants to categorize beers. It was derived from retrospective verbal protocols (Ericsson & Simon, 1993) because these protocols can be used to infer cognitive processes used by individuals to arrive at decisions. The first question

was: “Take time to remember the tasting experience you just had. Now, try to remember the last beer you have tasted, how was it ... Can you tell me what you did to decide that this beer was a top-fermented or a bottom-fermented beer?” The second question was: “You have just told me how you did to decide that the last beer was a top-fermented beer or a bottom-fermented beer. Did you follow the same procedure to decide the fermentation type of all the beers? If you did not proceed in the same way, can you describe the other scenario, referring to precise and concrete examples?” The third question was: “Can you give your sensory definition of a top-fermented beer and a bottom-fermented beer?” Finally, the fourth question was: “Before you answered this questionnaire, we have imagined different ways to decide whether a beer is a top- or a bottom-fermented one. We tried to convey these ideas into statements that are presented below. We ask you to read these statements carefully. For each one, we ask you to say whether YES, you have already used this procedure to decide on a beer fermentation type or whether NO, you have never used it.” Forty-two such statements were proposed to the participants. The statements were built based on hypotheses on the possible strategies that participants could have used to decide about the category membership of beers (Table 2).

**Table 2**  
Participants' answers for Question 4: percentages of participants who answered “yes I have already used this procedure to decide on a beer fermentation type” for each of the 42 proposed statements. The scenarios are sorted in decreasing order of the percentages of participants who answered “yes.”

Statements	Percentages of participants having answered “yes”
This beer is brown-colored. Its odor is quite strong in intensity. Its taste is rather strong and quite alcoholic. I infer it is a TF beer.	100.0
This beer is tasteless. I infer it is a BF beer.	94.4
This beer is blond-colored. Its odor is quite strong in intensity. Its taste is rather strong and quite alcoholic. I infer it is a TF beer.	89.5
This beer is brown-colored. Its odor is not very intense. It is tasteless and not very alcoholic. I infer it is a BF beer.	88.9
This beer has a quite strong taste. I infer it is a TF beer.	84.2
This beer is blond-colored. Its odor is not very intense. It is tasteless and not very alcoholic. I infer it is a BF beer.	84.2
This beer is not very alcoholic. I infer it is a BF beer.	83.3
This beer has a persistent after-taste. I infer it is a TF beer.	77.8
This beer is quite alcoholic. I infer it is a TF beer.	77.8
This beer is rather thick. I infer it is a TF beer.	77.8
This beer is brown-colored. I don't find any particular odor or taste. I infer it is a BF beer.	73.7
This beer is blond-colored. I don't find any particular odor or taste. I infer it is a BF beer.	72.2
This beer is blond-colored. I remember that I have already tasted it during previous sessions. I don't know its name but I know that it's a BF/TF beer.	44.4
This beer is quite bitter. I infer it is a TF beer.	42.1
This beer is quite sweet. I infer it is a TF beer.	42.1
I recognize this beer. I know its name. It's ( <i>name of the beer</i> ). I know that it's a BF/TF beer.	42.1
This beer has a quite intense malty taste. I infer it is a BF beer.	38.9
This beer has caramel, honey, spices and coffee aromas. I infer it is a TF beer.	36.8
This beer is brown-colored. I infer it is a TF beer.	36.8
This beer has fruity aromas (apple, banana...). I infer it is a TF beer.	31.6
This beer has a quite intense malty taste. I infer it is a TF beer.	31.6
This beer is quite sweet. I infer it is a BF beer.	31.6
This beer is quite bitter. I infer it is a BF beer.	27.8
This beer has floral aromas (lilac...). I infer it is a TF beer.	22.2
This beer is brown-colored. I don't find any particular odor or taste. I answer at random.	22.2
This beer is very sparkling. I infer it is a TF beer.	21.1
This beer has fruity aromas (apple, banana...). I infer it is a BF beer.	16.7
This beer is blond-colored. I infer it is a BF beer.	16.7
This beer has a strong yeasty taste. I infer it is a TF beer.	15.8
This beer is white-colored. I infer it is a BF beer.	15.8
This beer is white-colored. I infer it is a TF beer.	15.8
This beer is brown-colored. I know that brown-colored beers can be BF or TF beers. I answer at random.	15.8
This beer is very sparkling. I infer it is a BF beer.	15.8
This beer is blond-colored. I don't find any particular odor or taste. I answer at random.	11.1
This beer is blond-colored. I know that blond-colored beers can be BF or TF beer. I answer at random.	10.5
This beer is nor very sparkling. I infer it is a TF beer.	10.5
This beer is blond-colored. I infer it is a TF beer.	5.6
This beer is brown-colored. I infer it is a BF beer.	5.6
This beer has caramel, honey, spices and coffee aromas. I infer it is a BF beer.	5.3
This beer is very sparkling. I infer it is a BF beer.	5.3
This beer has floral aromas (lilac...). I infer it is a BF beer.	0.0
This beer has a strong yeasty taste. I infer it is a BF beer.	0.0



### 3. Results

For the learning data, participants' answers were coded into 1 and 0. For each tested beer, a value of 1 was recorded if the participant correctly identified the fermentation type and a value of 0 was recorded if not. Depending upon the questions, the questionnaire data were analyzed qualitatively or by calculating frequencies of answers.

#### 3.1. Analysis of the learning data

Our main hypothesis is: if participants have learned to identify the membership of the beers, then we will observe an increase in the proportion of correct answers from  $T_0$  to  $T_{final}$ . If this hypothesis is confirmed then two other hypotheses could be evaluated: 1) if participants have learned to identify the membership of each beer individually but failed to categorize other beers, then performance would be better at  $T_{final}$  than at  $T_0$  but only for the beers to which participants were exposed during the exposure stage (*learned* beers), 2) if participants succeeded in generalizing their categorization to other beers, then performance would be better at  $T_{final}$  than at  $T_0$  for the beers to which participants were exposed during the exposure stage (*learned* beers) and also for the beers to which they were not exposed to (*non-learned* beers).

The data were analyzed in three different ways: 1) in a global way by comparing  $T_0$  to  $T_{final}$  for all the beers at the same time, 2) by comparing  $T_0$  to  $T_{final}$  for each individual beer, 3) by studying the evolution of the data during the exposure sessions. Finally, confidence ratings given by the participants at  $T_0$  and  $T_{final}$  were analyzed and compared to the learning data.

##### 3.1.1. Data analysis at $T_0$ and $T_{final}$ for all the beers at the same time

Fig. 2 shows the percentages of correct answers obtained at the first ( $T_0$ ) and last ( $T_{final}$ ) sessions for the *learned* and *non-learned* TF and BF beers. Data were analyzed with a factorial analysis of variance (ANOVA) with a three within factor design: Session ( $T_0$  vs.  $T_{final}$ ), Learning (*learned* vs. *non-learned* beers), and Fermentation type (TF vs. BF). This analysis revealed an effect of learning [ $F(1,752) = 4.02$ ,  $MSe = 0.248$ ,  $p = .045$ ]. The percentage of correct answers for *learned* beers ( $M = 53.7$ ,  $SD = 22.7\%$ ) was globally higher than for *non-learned* beers ( $M = 46.3$ ,  $SD = 20.7\%$ ). A significant interaction between learning and session was also observed [ $F(1,752) = 4.64$ ,  $MSe = 0.248$ ,  $p = .031$ ]. Two Student  $t$ -tests between the mean participant answers at  $T_0$  and  $T_{final}$  for *learned* beers on the one side and for *non-learned* beers on the other side showed a significant difference in the number of correct answers between  $T_0$  and  $T_{final}$  for *learned* beers only [ $t(189) = 2.60$ ,  $p < .010$ ]. The number of correct answers for *learned* beers was significantly higher at  $T_{final}$  ( $M = 60.0$ ,  $SD = 21.8\%$ ) than at  $T_0$  ( $M = 47.4$ ,  $SD = 22.0\%$ ). These results indicate that participants learned to identify category membership for beers they tasted several times during the exposure sessions (*learned* beers) but were not able to generalize this learning to beers to which they were not exposed

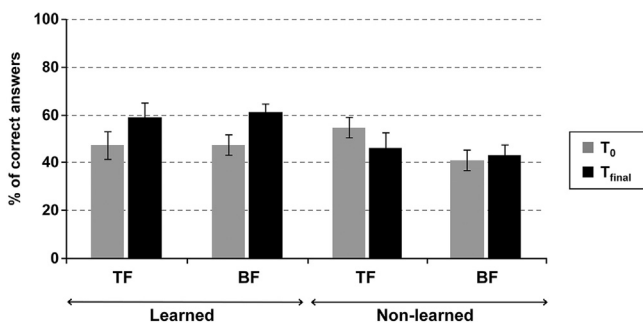


Fig. 2. Percentages of correct answers (mean  $\pm$  standard error) obtained for all the participants for TF and BF *learned* and *non-learned* beers at  $T_0$  and  $T_{final}$ .

(*non-learned* beers). In addition, there was no effect of the fermentation type, a pattern showing that one fermentation type (top or bottom) was not easier to categorize than the other, at  $T_0$  as well as at  $T_{final}$ .

##### 3.1.2. Data analysis at $T_0$ and $T_{final}$ for each individual beer

In order to specifically evaluate the results of the trap beers (Hoegaarden and “Bière du Démon”), data were also analyzed beer by beer. Fig. 3 shows the average results for each beer at  $T_0$  and  $T_{final}$ . This graph shows that for most of the beers (13 out of 20), the percentage of correct answers increased between  $T_0$  and  $T_{final}$ . Among these 13 beers, there are nine *learned* beers (the last *learned* beer, Bavaria 8.6, obtained the same results at  $T_0$  and  $T_{final}$ ). By contrast, performance decreased between  $T_0$  and  $T_{final}$  for the six following beers: Palm Special, Hoegaarden, Duvel, Wel Scotch, Bière du Démon, and Atlas. All these beers are *non-learned* beers, a result confirming again the influence of beer exposure during the exposure stage on the results at  $T_0$ . Among the four *non-learned* beers whose percentage of correct answers increased between  $T_0$  and  $T_{final}$ , two are TF beers (Saint Landelin and Jenlain) and two are BF beers (Stella Artois and Chti). Moreover, a binomial test (with  $P = \frac{1}{2}$ ) applied on the number of correct answers for each beer at  $T_0$  and  $T_{final}$  shows that five beers had a percentage of correct answers significantly higher than chance at  $T_{final}$ . These beers were four *learned* beers (Grain d’Orge, Heineken, Carlsberg, and 33 Export) and one *non-learned* beer (Jenlain). If we look at the two trap beers (Hoegaarden and Bière du Démon, striped on the graph), the percentage of correct answers decreased between  $T_0$  and  $T_{final}$  for Hoegaarden [ $t(18) = 2.05$ ;  $p = .050$ ] but not for Bière du Démon [ $t(18) = .89$ ;  $ns$ ].

##### 3.1.3. Analysis of the confidence ratings

We examined the confidence ratings collected from the participants after each answer at  $T_0$  and  $T_{final}$  to evaluate whether these ratings increased between the first and the last sessions. Fig. 4 shows the percentages of quotation of the three confidence marks (not sure/sure/very sure) at  $T_0$  and  $T_{final}$ . Fig. 4 shows that participants were more confident of their answers at  $T_{final}$  than at  $T_0$ : The percentage of quotation for the rating “not sure” is higher at  $T_0$  than at  $T_{final}$  [ $\chi^2(1, N = 1070) = 27.37$ ,  $p < .001$ ] whereas those for the ratings “sure” and “very sure” were higher at  $T_{final}$  than at  $T_0$  [respectively:  $\chi^2(1, N = 364) = 42.55$ ,  $p < .001$ ;  $\chi^2(1, N = 86) = 25.33$ ,  $p < .001$ ].

Moreover, we examined whether a relation existed between the confidence ratings and participants' answers at  $T_0$  and  $T_{final}$ . Specifically, we examined whether the participants' answers were more often correct when participants declared to be “very sure” than when they declared to be “not sure.” Fig. 5 shows the percentages of correct answers as a function of the confidence ratings given by the participants. We carried out two ANOVAs (one for the data at  $T_0$  data and one for the data at  $T_{final}$ ) with a one within factor design: Confidence rating (*not sure* vs. *sure* vs. *very sure*). At  $T_0$  there is no significant difference between the percentage of correct answers regardless of whether participants declare being “very sure” or “not sure” of their answer [ $F(2,377) = 0.38$ ,  $MSe = 0.251$ ,  $p = .686$ ] whereas at  $T_{final}$ , the percentage of correct answers is larger for high confidence answers [ $F(2,377) = 5.28$ ,  $MSe = 0.245$ ,  $p = .005$ ]. A Duncan test showed that the percentage of correct answers when participants were very sure was significantly higher ( $M = 68.42\%$ ) than when they were not sure ( $M = 45.41\%$ ).

#### 3.2. Analysis of the questionnaire

The objective of this questionnaire was to identify the strategies used by the participants to decide about the beers' category membership. Participants' answers were studied qualitatively, except for Questions 3 and 4. For Question 3 we calculated the percentage of quotation of each term or expression. For Question 4 we computed the percentage of participants who have chosen each statement.

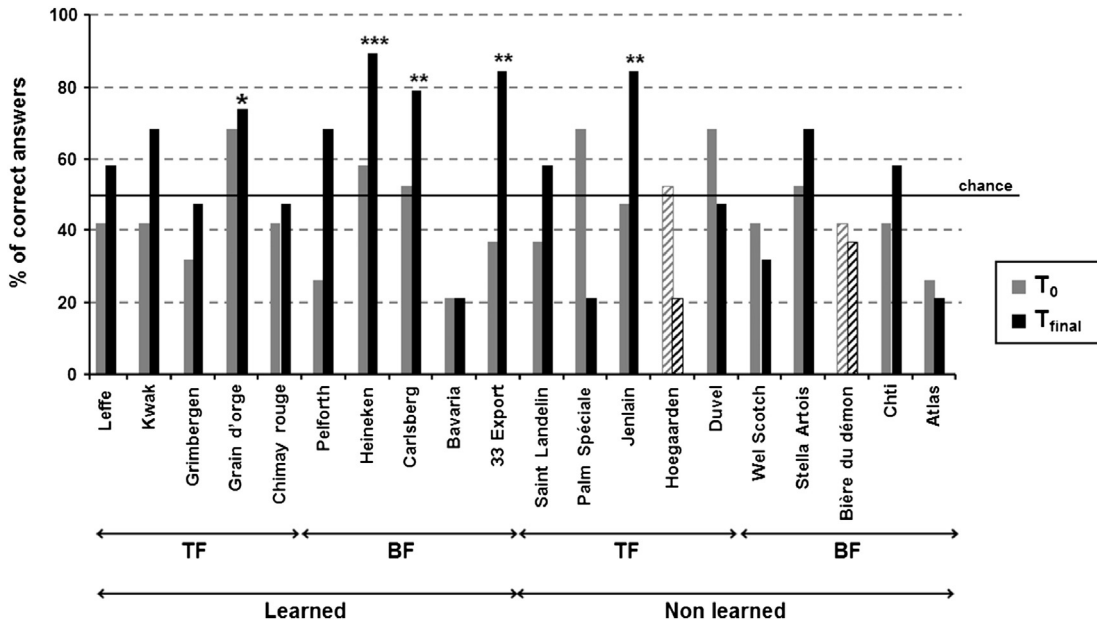


Fig. 3. Percentages of correct answers obtained by the group of participants for TF and BF learned and non-learned beers at T<sub>0</sub> and T<sub>final</sub>. The trap beers are striped. The stars show the probability level associated with the binomial test ( $P = 1/2$ ): \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$ . The horizontal line shows the percentage of correct answers for random guessing (i.e., 50% correct answers).

For Question 1—which asked the participants to describe the way they had proceeded to decide on the fermentation type of the last tested beer—a consensus stands out: All participants reported that when they tasted a beer whose taste was persistent, quite alcoholic, sweet, quite aromatic, bitter or heavy, they inferred that it was a TF beer. By contrast, when participants tasted a non-persistent, low-alcohol beer, with relatively few aromas or taste, and little sparkling, they decided that it was BF beer. For example, one participant explained that he found that his beer was similar to a “Heineken or 33 Export beer” and so, as he knew (with the exposure sessions) that these two beers were BF beers, he inferred that his beer was a BF beer too.

For Question 2—which asked participants if they have proceeded in the same way to decide on the fermentation type of all the beers—most of the participants (18 participants out of 19) replied “yes.” Only one participant explained that he had changed his criteria of decision along the sessions. Another participant explained:

“Yes, I compare it to beers that I know. By regularly tasting beers we remember which beer brand was BF and TF. Then when we taste other beers we compare. Moreover we build up ourselves an opinion because in general TF beers are more alcoholic, more aromatic, more persistent and thicker. On the contrary, BF beers are more acidic, less alcoholic, less persistent and less thick. For some beers which are close to both BF and TF beers, it is difficult to decide.”

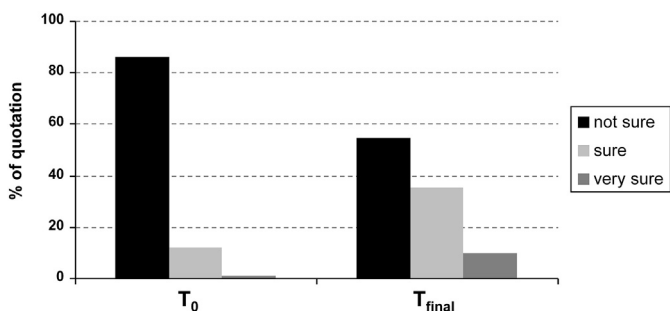


Fig. 4. Percentages of quotation for each confidence mark (not sure/sure/very sure) for the group of participants at T<sub>0</sub> and T<sub>final</sub>.

Another participant indicated that his decision was based on the sugar/alcohol combination, another participant reported using the aromatic wealth, the persistence and the alcohol degree, yet another mentioned “the global effect in the mouth (persistence and bitterness),” and finally one participant indicated that color was important.

Question 3 asked the participants to provide their sensory definition of TF and BF beers. For TF beers, 63% of the participants used *persistent* and *alcoholic*, 47% *sweet*, “strong flavor” and “a lot of aromas” and 26% of the participants used *thick* and *bitter*. The other terms cited less often by the participants, were (in descending order of the percentage of quotation): *round*, *darker color*, *sparkling*, *malty taste*, *spices*, *amber*, *more acidic*. The BF beers were described as *not very persistent*, *not very tasty*, and *not very alcoholic* by 42% of the participants and as being *often blond* by 26% of the participants. The other terms used by the participants were (in descending order): *not very sweet*, *not very aromatic*, *not very sparkling*, *not very acidic*, *more bitter*, *less bitter*, *not very fizzy*, *watery taste*, *acidic*. It seems that the participants were rather in agreement on the sensory descriptions of TF and BF beers, especially for TF beers. For BF beers, the participants showed less agreement, especially for the terms *acidic* and *bitter*.

Finally in Question 4, participants had to indicate if they had used the proposed procedures to decide upon the fermentation type of the beers

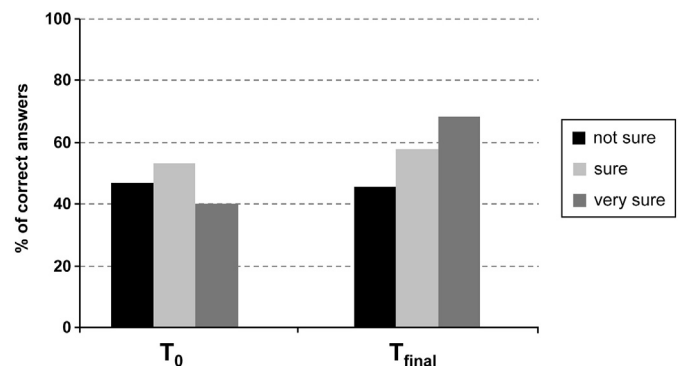


Fig. 5. Percentages of correct answers obtained when participants declared to be “not sure,” “sure,” and “very sure” of their answers, at T<sub>0</sub> and T<sub>final</sub>.

that they had tasted. The percentage of participants having answered “yes” for each of the 42 procedures is given in Table 2.

On the whole, Table 2 reveals results consistent with those from Questions 1 and 3. Participants seemed to agree to say that TF beers are alcoholic, with a strong flavor, persistent and thick. By contrast, BF beers were perceived as not very alcoholic and relatively tasteless.

Interestingly, the beer color did not appear to constitute a decision-making criterion by itself. Only 17% of the participants declared having used the blond color of a beer to infer that it was a BF beer and 6% that it was TF. For the dark color, 37% of the participants declared having inferred that the beer was a TF beer by looking at its dark color versus 6% of the participants who inferred that it was a BF beer. So it seems that when a beer was dark, the participants decided that it was produced by the top fermentation, although this criterion did not seem to be sufficient by itself. Concerning the wheat beers, 16% of the participants decided that they were BF beers and 16% BF beers. The sweetness seems to be a key criterion because 74% of the participants used it at least one time to decide on the fermentation type (“This beer is rather sweet, I infer it is a BF/TF beer”). Among these participants, 42% used a sweet taste to decide that a beer was a TF beer and 32% to decide that it was a BF beer. This pattern shows that the participants did not agree on the decision value of the sweet taste of a beer and that this criterion is not sufficient to determine the fermentation type. Sparkling is a criterion on which we had no a priori hypothesis. It seems that the participants evaluated a very sparkling beer as being rather a TF beer and a not very sparkling beer as being a BF beer but this criterion was neither very consensual nor decisive in the category choice. Indeed, only 21% of the participants decided that a very sparkling beer was a TF beer versus 5% of the participants who decided that it was a BF beer, and only 16% of the participants decided that a not very sparkling beer was a BF beer against 11% who decided that it was a TF beer. Bitterness was another criterion on which we had no hypothesis a priori. Most of the participants (70%) reported that they had used it at least once to decide on the fermentation type, among them 42% inferred that a bitter beer was a TF beer and 28% inferred that it was a BF beer. Similarly 53% of the participants mentioned that they had used at least once “malty” as a cue as indicated by: “this beer has a quite strong malty taste, I infer it is a BF/TF beer.” Among these participants, 16% used malty to decide that a beer was a TF beer, 21% to decide that it was a BF beer, and 16% to decide that a beer was sometimes a BF beer and sometimes a TF beer. So it seems that there is no consensus on the importance of the malty taste in a beer for the fermentation type decision. Finally 58% of the participants said that they had already recognized the beer and inferred its fermentation type. Among them, 42% say that they had remembered the beer name.

#### 4. Discussion

The present study sought to better understand the phenomenon of category learning in the chemosensory field. Previous studies on wine suggest that, through repeated exposure to wines, experts develop wine categorical knowledge organized around prototypes based on correlational characteristics of wine aromas from different grape varieties or different colors (Ballester, Abdi, Langlois, Peyron, & Valentin, 2009; Ballester et al., 2005, 2008; Brochet & Dubourdieu, 2001; Gawel, 1997; Hughson, 2003; Hughson & Boakes, 2001, 2002; Morot, Brochet, & Dubourdieu, 2001; Parr et al., 2007, 2010; Solomon, 1997). In the present study, we tested whether repeated exposure with feedback to beers was enough for beer consumers to learn beer sensory categories and we also explored the underlying mechanisms of this learning.

##### 4.1. Is a repeated exposure followed by a feedback sufficient to learn beer categories?

We found that participants' results were better at  $T_{\text{final}}$  than at  $T_0$  for learned beers only (60% vs. 47% of correct answers respectively), a

pattern suggesting that participants learned to identify the category membership of beers to which they had been exposed but were not able to generalize their learning to other beers.

The fact that participants were not able to generalize to other beers is congruent with perceptual learning theory (Goldstone, 1998; Kellman & Garrigan, 2009). Transfer of perceptual learning to other stimuli or tasks different from those used during training seems to be difficult. This limit has been previously noted in the beer domain by Chollet, Valentin, and Abdi (2005) who found that perceptual superiority of beer trained assessors in discriminative tasks was limited to the beers on which they were trained. This difficulty to generalize might have been due to the small number of beers to which participants have been exposed (especially taking into account that the categories were, in addition, deliberately chosen to be ill-defined). By contrast, professionals having taken part in previous studies on wines (Ballester et al., 2005, 2008, 2009; Hughson & Boakes, 2002; Solomon, 1997) had several years of experience in their domain, and, so, had been frequently exposed to a lot of different exemplars of each wine category. Our participants, however, were presented with only 13 beers of each category (5 learned beers and 8 new beers), the learned beers having been repeated three times and the new beers only once.

Category learning in everyday life occurs from the youngest age—two to three months' old—(Arterberry & Bornstein, 2001; Mandler, 1992) and is strongly associated with a goal oriented learning context (Lynch et al., 2000). By contrast, in the present study, participants were students and the experiment was included in a course on brewery techniques and it is possible that this rather scholastic context and somewhat “aseptic” tasting place (a sensory analysis room with individual boxes) did not create the best learning environment for complex natural categories such as type of fermentation. Besides, we observed that although participants were informed of the scientific importance of this study, some participants—three participants reported it—had grown tired along the sessions and were perhaps not completely involved at the end of the study.

##### 4.2. Which strategies are implied in beer category learning?

An additional objective of this study was to get some clues to formulate hypotheses regarding the underlying chemosensory category learning strategies. Participants' answers to the questionnaire revealed areas of consensus on the beer sensory properties of each category. Top-fermented beers were frequently described as quite alcoholic, persistent, with a strong taste, and being quite thick. Bottom-fermented beers were described as being rather low-alcoholic, tasteless, and not very persistent. These results suggest that participants could have built some rules about the sensory properties of beers. According to Close et al. (2010), a rule is some sort of general statement or principle that specifies definitely whether an object or event is of particular sort or not. One important aspect of a rule is that membership in a category is clear-cut: Either an element has all the necessary characteristics and it is a member of the category or it lacks one or more of the characteristics and it is not a member of the category. In our case, an example of rule would be a statement such as “All the dark beers are top-fermented beers” or “If a beer is blond and low-alcoholic, it is a bottom-fermented beer.”

Alternatively, participants could have built a beer prototype for each category from the regularities that they captured during the exposure sessions. The prototype for TF beers would be quite alcoholic, with a strong and persistent taste, whereas the prototype for BF beers would be a low-alcoholic and tasteless beer. Then participants would categorize beers into TF or BF beer categories by comparing beers to the category prototypes. However, the predictions made by these two scenarios are difficult to disentangle: Because we used a declarative task to access participants' strategies, the verbal description of a prototype might be incorrectly interpreted as a rule.



Furthermore, the fact that participants agreed on a number of common sensory properties and that participants declared having used some procedures such as: “This beer is brown-colored. Its odor is quite strong in intensity. Its taste is strong and quite alcoholic. I infer that it is a TF beer” could also imply that the participants compared the sensory characteristics of a beer to be categorized to those of the category beers, a strategy akin to the feature frequency model (Kellogg, 1981; Neumann, 1974; Reed, 1972). These different models (rules, prototype, and feature frequency) assume that people use abstracted information to classify novel elements. Prototype theories have been most successful in predicting how people will classify perceptual patterns consisting of feature values that vary continuously along a dimension whereas the feature frequency theory has been most successful in predicting how people classify patterns consisting of feature values that do not vary continuously along a dimension (Kellogg, Bourne, & Ekstrand, 1978; Reed, 1972; Strauss, 1979).

Our data did not bring evidence in favor of one particular strategy or the other. However, because participants were asked during the exposure phase to quickly describe the beers, it is possible that we biased them in the direction of the feature frequency model by asking them to concentrate themselves on the sensory characteristics of beers. Either way, the fact that the participants were not able to generalize to *non-learned* beers could then show that the abstracted information (prototype or features) was not precise enough to enable participants to correctly identify the category membership of other beers. Another result in favor of the statistical learning hypothesis concerns the trap beers—which were beers from one category with sensory characteristics closer to the other category. For two trap beers (Hoegaarden and Bière du Démon), the percentages of correct answers did not increase between  $T_0$  and  $T_{\text{final}}$ , (and in fact even decreased for Hoegaarden). If we suppose that participants were sensitive to sensory regularities and began to extract information from these regularities, the results observed for the trap beers can be interpreted in terms of over-generalization. This effect was highlighted in a well-known effect reported—among others—by Brown (1973), (see also the “neural-network” simulations of Rumelhart and McClelland (1986)) dealing with learning the past tenses of English verbs by children. This type of learning displays a U-shaped curve: First, children perform correctly by mimicking the environment; then, when they realize that there is a rule (add “-ed”), they initially tend to over-generalize its application (e.g., “I goed”) and their performance deteriorates. Only after some time do children learn that some verbs are regular and others are irregular and their performance improves again. In our case, participants began to learn to correctly categorize beers into TF and BF beer categories by extracting sensory regularities, but when faced later on with trap beers whose sensory characteristics did not match the target category, participants failed to correctly classify them. However, if participants had used a prototype strategy to classify the beers, we would probably observe an increased number of correct answers at  $T_{\text{final}}$  compared to  $T_0$  for Stella Artois. In fact this *non-learned* beer is very similar to the three *learned* beers 33 Export, Heineken, and Carlsberg whose proportion of correct classifications significantly increased at  $T_{\text{final}}$  compared to  $T_0$ .

A third possible strategy would be that the participants memorized each individual beer and its category. Some answers of the participants to the questionnaire tend to confirm this hypothesis, in particular the fact that 58% of the participants declared having already recognized a beer and having inferred its category (“This beer is blond-colored. I remember that I have already tasted it during previous sessions. I don’t know its name but I know that it is a BF/TF beer” or “I recognize this beer. I know its name. It is (name of the beer). I know that it is a BF/TF beer”). This hypothesis is further supported by some accounts such as when a participant explained that he found that his beer looked like the 33 Export or the Heineken beers and who inferred that it was a BF beer because he knew that 33 Export and Heineken are BF beers. This kind of reasoning would be congruent with the exemplar theory

(Nosofsky, 1992) which posits that people memorize category exemplars and that a new element is categorized by comparison with these exemplars. The fact that the participants were not able to generalize to the *non-learned* beers could then show that the number of exemplars stored in memory was too small to provide a complete view of the categories.

Finally, the fact that our results are compatible with different theories also suggests that not all participants used the same strategies or that participants used several strategies simultaneously as suggested by Pinker (1991) for past tense learning. This author defends that the way children learn the preterit tense can be interpreted with a dual mechanism: learning the preterit tense of regular verbs would be produced by a mechanism based on rules whereas the preterit tense of irregular verbs would be stored in an associative memory system. So it is possible that some participants would extract sensory regularities and then build beer prototypes but in parallel would store beer exemplars in memory. Our protocol cannot, unfortunately, dissociate these different mechanisms and further research is needed in this direction.

## 5. Conclusion

This study demonstrated that participants have improved their performance to identify the category membership of beers by being repeatedly exposed with feedback to these beers but are not able to generalize this learning to other beers. The retrospective verbal protocol questionnaire used to assess participants’ learning strategies suggests that exemplar-similarity and feature-frequency models might provide a better account of our results than the prototype abstraction model suggested in previous work (Ballester et al., 2005, 2008, 2009; Brochet & Dubourdieu, 2001; Gawel, 1997; Hughson, 2003; Hughson & Boakes, 2001, 2002; Morot et al., 2001; Parr et al., 2007, 2010; Solomon, 1997). The main contribution of this paper is thus to question the well-established idea in chemosensory perception that foods or beverages are represented in memory as prototypes abstracted from repeated exposures. The next step will be to confirm this interpretation and to explore further the ability of exemplar-similarity and feature-frequency models to predict chemosensory categorization data.

## Acknowledgements

HA would like to acknowledge the support of an EURIAS fellowship at the Paris Institute for Advanced Studies (France), with the support of the European Union’s 7th Framework Program for research, and from a funding from the French State managed by the “Agence Nationale de la Recherche (program: Investissements d’avenir, ANR-11-LABX-0027-01 Labex RFIEA+).”

## References

- Arterberry, M. E., & Bornstein, M. H. (2001). Three-month-old infants’ categorization of animals and vehicles based on static and dynamic attributes. *Journal of Experimental Child Psychology*, 80, 333–346. <http://dx.doi.org/10.1006/jecp.2001.2637>.
- Ashby, F. G., & Maddox, W. T. (2005). Human category learning. *Annual Review of Psychology*, 56, 149–178. <http://dx.doi.org/10.1146/annurev.psych.56.091103.070217>.
- Ballester, J., Abdi, H., Langlois, J., Peyron, D., & Valentin, D. (2009). The odor of colors: Can wine experts and novices distinguish the odors of white, red, and rosé wines? *Chemosensory Perception*, 2, 203–213. <http://dx.doi.org/10.1007/s12078-009-9058-0>.
- Ballester, J., Dacremont, C., Le Fur, Y., & Etiévant, P. (2005). The role of olfaction in the elaboration and use of the Chardonnay wine concept. *Food Quality and Preference*, 16, 351–359. <http://dx.doi.org/10.1016/j.foodqual.2004.06.001>.
- Ballester, J., Patris, B., Symoneaux, R., & Valentin, D. (2008). Conceptual vs. perceptual wine spaces: Does expertise matter? *Food Quality and Preference*, 19, 267–276. <http://dx.doi.org/10.1016/j.foodqual.2007.08.001>.
- Brochet, F., & Dubourdieu, D. (2001). Wine descriptive language supports cognitive specificity of chemical senses. *Brain and Language*, 77, 187–196. <http://dx.doi.org/10.1006/brln.2000.242>.
- Brown, R. (1973). *A first language*. Cambridge (USA): Harvard University Press.
- Candolon, M., Ballester, J., Uscida, N., Blanquet, J., & Le Fur, Y. (2004). Sensory methodology developed for investigation of Sciaccarello wine concept. *Journal International des Sciences de la Vigne et du Vin*, 38, 147–154.
- Chase, W. C., & Simon, H. A. (1973). Perception in Chess. *Cognitive Psychology*, 4, 55–81.



- Chatard-Pannetier, A., Brauer, M., Chambres, P., & Niedenthal, P. (2002). Représentation, catégorisation et évaluation: différence entre experts et novices dans le domaine des meubles d'antiquité. *L'Année Psychologique*, 102, 423–448. <http://dx.doi.org/10.3406/psy.2002.29600>.
- Chi, M., Feltovich, P. J., & Glaser, R. (1981). Categorization and representation of physics problem by experts and novices. *Cognitive Science*, 5, 121–152. [http://dx.doi.org/10.1207/s15516709cog0502\\_2](http://dx.doi.org/10.1207/s15516709cog0502_2).
- Chollet, S., Valentin, D., & Abdi, H. (2005). Do trained assessors generalize their knowledge to new stimuli? *Food Quality and Preference*, 16, 13–23. <http://dx.doi.org/10.1016/j.foodqual.2003.12.003>.
- Close, J., Hahn, U., Hodgetts, C. L., & Pothos, E. M. (2010). Rules and similarity in adult concept learning. In D. Mareschal, P. C. Quinn, & S. E. G. Lean (Eds.), *The making of the human concepts* (pp. 29–51). New York: Oxford University Press.
- Conway, C. M., & Christiansen, M. H. (2005). Modality-constrained statistical learning of tactile, visual and auditory sequences. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 31, 24–39. <http://dx.doi.org/10.1037/0278-7393.31.1.24>.
- Dukes, W. D., & Bevan, W. (1967). Stimulus variation and repetition in the acquisition of naming responses. *Journal of Experimental Psychology*, 74, 178–181. <http://dx.doi.org/10.1037/h0024575>.
- Ericsson, K. A., & Simon, H. A. (1993). *Protocol analysis: Verbal reports as data* (2nd ed.). Cambridge, MA: The MIT Press.
- Fiser, J., & Aslin, R. N. (2001). Unsupervised statistical learning of higher-order spatial structures from visual scenes. *Psychological Science*, 12, 499–504. <http://dx.doi.org/10.1111/1467-9280.00392>.
- Gawel, R. (1997). The use of language by trained and untrained experienced wine tasters. *Journal of Sensory Studies*, 12, 267–284. <http://dx.doi.org/10.1111/j.1745-459X.1997.tb00067.x>.
- Gibson, E. J. (1969). *Principles of perceptual learning and development*. New York: Appleton-Century-Crofts.
- Goldstone, R. L. (1998). Perceptual learning. *Annual Review of Psychology*, 49, 585–612. <http://dx.doi.org/10.1146/annurev.psych.49.1.585>.
- Goldstone, R. L., & Kersten, A. (2003). Concepts and categorization. In A. F. Healy, & R. W. Proctor (Eds.), *Comprehensive handbook of psychology. Experimental psychology*, 4. (pp. 599–621). New York: Wiley.
- Honeck, R. P., Firment, M., & Case, T. J. (1987). Expertise and categorization. *Bulletin of the Psychonomic Society*, 25, 431–434.
- Hughson, A. L. (2003). Wine expertise: Current theories and findings regarding the nature and bases of wine expertise. *Food Australia*, 55, 193–196.
- Hughson, A. L., & Boakes, R. A. (2001). Perceptual and cognitive aspects of wine expertise. *Australian Journal of Psychology*, 53, 103–108. <http://dx.doi.org/10.1080/00049530108255130>.
- Hughson, A. L., & Boakes, R. A. (2002). The knowing nose: the role of knowledge in wine expertise. *Food Quality and Preference*, 13, 463–472. [http://dx.doi.org/10.1016/S0950-3293\(02\)00051-4](http://dx.doi.org/10.1016/S0950-3293(02)00051-4).
- Hull, C. L. (1920). Quantitative aspects of the evolution of concepts. *Psychological Monographs*, 28, 1–86.
- Kellman, P. J., & Garrigan, P. (2009). Perceptual learning and human expertise. *Physics of Life Review*, 6, 53–84. <http://dx.doi.org/10.1016/j.plrev.2008.12.001>.
- Kellogg, R. T. (1981). Feature frequency in concept learning: What is counted? *Memory and Cognition*, 9, 157–163. <http://dx.doi.org/10.3758/BF03202330>.
- Kellogg, R. T., Bourne, L. E., & Ekstrand, B. R. (1978). Feature frequency and the acquisition of natural concepts. *American Journal of Psychology*, 91, 211–222.
- Lu, Z. -L., Hua, T., Huang, C. -B., Zhou, Y., & Doshier, B. (2011). Visual perceptual learning. *Neurobiology of Learning and Memory*, 95, 145–151. <http://dx.doi.org/10.1016/j.nlm.2010.09.010>.
- Lynch, E. B., Coley, J. D., & Medin, D. L. (2000). Tall is typical: Central tendency, ideal dimensions and graded category structure among tree experts and novices. *Memory and Cognition*, 28, 41–50. <http://dx.doi.org/10.3758/BF03211575>.
- Mandler, J. M. (1992). How to build a baby: Conceptual primitives. *Psychological Review*, 99, 587–604. <http://dx.doi.org/10.1037/0033-295X.99.4.587>.
- Medin, D. L., & Shaffer, M. M. (1978). Context theory of classification learning. *Psychological Review*, 85, 207–238. <http://dx.doi.org/10.1037/0033-295X.85.3.207>.
- Morot, G., Brochet, F., & Dubourdieu, D. (2001). The colors of odors. *Brain and Language*, 79, 309–320. <http://dx.doi.org/10.1006/brln.2001.2493>.
- Neumann, P. G. (1974). An attribute frequency model for the abstraction of prototypes. *Memory and Cognition*, 2, 241–248. <http://dx.doi.org/10.3758/BF03208990>.
- Nosofsky, R. M. (1988). Exemplar-based accounts of relations between classification, recognition, and typicality. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 14, 700–708. <http://dx.doi.org/10.1037/0278-7393.14.4.700>.
- Nosofsky, R. M. (1992). Exemplar-based approach to relating categorization, identification, and recognition. In F. G. Ashby (Ed.), *Multidimensional models of perception and cognition* (pp. 363–394). Hillsdale: Erlbaum.
- Parr, W. V., Green, J. A., White, K. G., & Sherlock, R. R. (2007). The distinctive flavor of New Zealand Sauvignon blanc: Sensory characterization by wine professionals. *Food Quality and Preference*, 18, 849–861. <http://dx.doi.org/10.1016/j.foodqual.2007.02.001>.
- Parr, W. V., Valentin, D., Green, J. A., & Dacremont, C. (2010). Evaluation of French and New Zealand Sauvignon wines by experienced French wine assessors. *Food Quality and Preference*, 21, 56–64. <http://dx.doi.org/10.1016/j.foodqual.2009.08.002>.
- Pinker, S. (1991). Rules of language. *Science*, 253, 530–535. <http://dx.doi.org/10.1126/science.1857983>.
- Posamentier, M., & Abdi, H. (2003). Processing faces and facial expressions. *Neuropsychology Review*, 13, 113–144. <http://dx.doi.org/10.1023/A:1025519712569>.
- Posner, M. I., & Keele, S.W. (1968). On the genesis of abstract ideas. *Journal of the Experimental Psychology*, 77, 353–363. <http://dx.doi.org/10.1037/h0025953>.
- Reed, S. K. (1972). Pattern recognition and categorization. *Cognitive Psychology*, 3, 382–407.
- Rouder, J. N., & Ratcliff, R. (2006). Comparing exemplar- and rule-based theories of categorization. *Current Directions in Psychological Science*, 15, 9–13. <http://dx.doi.org/10.1111/j.0963-7214.2006.00397.x>.
- Rumelhart, D. E., & McClelland, J. L. (1986). On learning the past tenses of English verbs. In J. L. McClelland, & D. E. Rumelhart (Eds.), *Parallel distributed processing: Explorations in the microstructure of cognition, vol. II*. (pp. 216–271). Cambridge: MIT Press.
- Saffran, J. R., Aslin, R. N., & Newport, E. L. (1996). Statistical learning by 8-month-old infants. *Science*, 274, 1926–1928. <http://dx.doi.org/10.1126/science.274.5294.1926>.
- Saffran, J. R., Johnson, E. K., Aslin, R. N., & Newport, E. L. (1999). Statistical learning of tone sequences by adults and infants. *Cognition*, 70, 27–52. [http://dx.doi.org/10.1016/S0010-0277\(98\)00075-4](http://dx.doi.org/10.1016/S0010-0277(98)00075-4).
- Shafto, P., & Coley, J. D. (2003). Development of categorization and reasoning in the natural world: Novices to experts, naïve similarity to ecological knowledge. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 29, 641–649. <http://dx.doi.org/10.1037/0278-7393.29.4.641>.
- Smith, E. E., & Sloman, S. A. (1994). Similarity- versus rule-based categorization. *Memory and Cognition*, 32, 377–386.
- Solomon, G. E. A. (1997). Conceptual change and wine expertise. *The Journal of the Learning Sciences*, 6, 41–60. [http://dx.doi.org/10.1207/s15327809jls0601\\_3](http://dx.doi.org/10.1207/s15327809jls0601_3).
- Strauss, M. S. (1979). Abstraction of prototypical information by adults and 10-month-old infants. *Journal of Experimental Psychology: Human Learning and Memory*, 5, 618–632. <http://dx.doi.org/10.1037/0278-7393.5.6.618>.
- Tanaka, J. W., & Taylor, M. (1991). Object categories and expertise: Is the basic level in the eye of the beholder? *Cognitive Psychology*, 23, 457–482. [http://dx.doi.org/10.1016/0010-0285\(91\)90016-H](http://dx.doi.org/10.1016/0010-0285(91)90016-H).
- Wright, B. A., & Zhang, Y. (2009). A review of the generalization of auditory learning. *Philosophical Transactions of the Royal Society, B: Biological Sciences*, 364(1515), 301–311. <http://dx.doi.org/10.1098/rstb.2008.0262>.