Effect of carbonation level on the perception of sourness in sparkling wine

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Abstract

The relationship between instrumental and sensory measurements were investigated in 11 wines varying in their carbonation level. Although sourness intensities of the wines were not significantly different, increased carbonation concentration affected the dynamics of sourness perception. Both the onset and extinction of the sourness perception were delayed with increased carbonation. Amongst potential explanations are that dynamic effects of carbonation draw attention away from sensations that arise in other sensory modalities, including gustation, and that carbonation has an anaesthetizing effect which partially reduces the ability to perceive sourness. Findings suggest potential for further research for systematically investigating how carbonation level affect how products are perceived in mouth.

Introduction

From a sensory perspective, sparkling wines are highly complex products. Carbonation increases surface area and kinetic energy. It also imparts characteristic mouthfeel effects that include tingling and other sensations, and may trigger gustatory, olfactory, trigeminal, and auditory perceptions as well [1]. A mechanism for carbonation perception as sourness has been proposed [2]. The effect of carbonation on the perception of sourness intensity (as determined using static sensory measurements) has been investigated in various beverages but reported results are inconsistent [3-8]. Although effects on sourness intensity are often reported to be slight, overall impact of carbonation may have a more pronounced effect on taste quality perceptions, e.g. on sweet and salty perception [9].

In a previous study, eleven wines with different carbonation levels were created [10] then evaluated according to a replicated experimental design by trained assessors using (i) sensory descriptive analysis (which provides static data on attribute intensities), and (ii) temporal check-all-that-apply (TCATA) [11] in which attribute applicability is determined dynamically over time.

Specifically, a trained descriptive sensory panel (n=11) conducted a replicated evaluation of the eleven wines according to the intensities of 20 sensory attributes. The panel discriminated wines based on 12 of the attributes (9 mouthfeel, 1 aroma, 1 flavour, and 1 taste), but the wines were not discriminated according to their sourness intensities [1]. TCATA data from trained assessors (n=12) indicated that the duration during which sensations are elicited is elongated with increasing carbonation concentration, yet the average citation rates for sourness (proportional to the area under the curve) were not significantly different across carbonation levels.

In this study, we further investigate these data to determine potential relationships between carbonation level in sparkling wine and the dynamic perception of sourness.

Experimental

Materials

Eleven wines were made starting from the same base cuvee, resulting in one (still) base wine and ten sparkling wines, each at a different carbonation level (1.2-7.5 g CO_2/L), using materials and winemaking techniques described in [10]. Wine chemistry analysis confirmed differences amongst samples with respect to carbonation, as well as similarity in terms of sensory threshold levels in recorded concentrations of total sugars, titratable acid, pH, and ethanol [10].

Sensory evaluation

Twelve assessors evaluated the 11 wines in triplicate via TCATA using eight attributes: six mouthfeel attributes (Bite/Burn, Carbonation/Bubble pain, Foamy, Numbing, Prickly/Pressure, Tingy) and two taste attributes (Bitter, Sour). The evaluation period was 120 s. Details related to attribute definitions, training, sample evaluation protocols, and other experimental parameters are found in [1].

Statistical analysis

TCATA curves were obtained for sourness citation rates per CO_2 level using the R package tempR [12]. Cumulative citation rates leading up to 15, 30, 45, 60, and 75 s were obatined per CO_2 level and stacked, such that rows indicated unique combinations of CO_2 level and time for both the predictor matrix (with variables ethanol, CO_2 concentration, titratable acidity) and response variables (TCATA citation rate for the eight TCATA attributes). These X and Y matrices were then submitted to multivariate PLS regression using the plsreg2 function in the R package plsdepot [13].

The predictor variable CO_2 level and response variable sourness citation rates per 15-s interval were submitted to least squares regression to investigate how sourness characterization changes with CO_2 level and time.

Results and discussion

TCATA curves for sourness citation rates per CO_2 level are presented in Figure 1. In this figure, we are looking at aggregated raw panel data in which the sourness curves are right-shifted and damped as the CO_2 concentration increases. Increased carbonation delayed the perceptual onset and extinction of sourness.



Figure 1: TCATA curves for the attribute Sour for the eleven samples which varied in CO₂ concentration.

Multivariate PLS-regression analysis gives correlations between the predictor and response variables; the relationships in the first two latent vectors are given in Figure 2, and show a temporal relationship between CO_2 concentration and time for sourness characterization.



Figure 2: Partial least squares regression analysis of analytical measurements (Titratable Acidity, CO_2 , and Ethanol) vs. TCATA Citation Proportion for 15-s intervals leading up to 15, 30, 45, 60, and 75 s. For each attribute shown these five time intervals are joined. The line that starts at 15 s and kinks at each time interval, with the closed square indicating 30 s, the open square 60 s, and the cumulating arrow (which indicate the progression of time) 75 s. Sour, which was the focus of this paper, is shown as a thick blue line.

Results from least squares regression indicate a strong relationship between sourness citation proportion and time. The proportion of assessors describing the wine as sour is highest in the 15-s interval leading up to 30 s across all CO_2 concentrations. There is significant interaction between time and CO_2 concentration (which is visualized here as differences in slopes). Leading up to 30 s, assessors describe low- CO_2 wines as sour more often than high- CO_2 wines; thereafter, the low- CO_2 wines are described as sour less often than high- CO_2 wines. Thus, the sourness citation proportion depends on both time and CO_2 concentration.

The wines described herein are similar in pH [10] and perceived intensity of sourness [1], yet differ in dynamic perception of sourness. Why might low-CO₂ wines be characterized as sour early, more often, and for a shorter duration, and high-CO₂ wines be characterized as sour later, less often, but for a longer duration? Potential explanations include the possibility that CO₂ has a masking or distracting effect (e.g. dynamic effects

of carbonation draw attention away from sensations that arise in other sensory modalities) or an anaesthetizing effect (e.g. carbonation partially reduces the ability to perceive sourness). Additionally, the right-shifted curves in Figure 1 may indicate adaptation, with perceived sourness attenuating after initial perception. Findings are relevant to product developers working on carbonated products, and suggest potential for further research for systematically investigating how carbonation level interacts with other wine components at different concentrations to affect how products are perceived in mouth.



Figure 3: Interaction plot showing cumulative TCATA Citation Proportion for the 15-s intervals leading up to 15, 30, 45, 60, and 75 s vs. CO₂ concentration. The observed citation proportions are shown in black, and slopes are presented in red.

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