Title

Category Analysis of California Petite Sirah (Durif): Does price affect the sensory attributes of these wines?

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Category Analysis of California Petite Sirah (Durif): Does price affect the sensory attributes of these wines?

By

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Abstract

We purchased 21 California Petite Sirah wines, all from vintages 2017-2020 and from Lodi, Paso Robles, Napa Valley, Sonoma County, the Sierra Foothills, Mendocino, and California. Price ranges were High (H) more than $40 per 750 mL bottle (5 wines), Medium (M) $20-$40 per bottle (9 wines), and Low (L) less than $20 a bottle (7 wines). A trained panel of 10 judges evaluated each wine in triplicate in a balanced randomized order for 29 sensory attributes. All attributes were anchored with reference standards. Data were analyzed via XLSTAT and RStudio.

Nineteen attributes were significantly different across the wines. Most wines were quite similar with some noted exceptions. These exceptional wines tended to be very high in the following attributes: barnyard, cooked vegetable, earthy, and smoky. The effect of price was only significant for three attributes, namely acetone with the L-wines having the lower acetone scores; sweet with the H-wines being perceived as sweeter; and hot with the H- and M-wines being perceived as hotter. The sweet perception result was not supported by the glucose and fructose concentration of the wines since the L-wines had significantly more of these compounds. It is possible that the perceived sweetness was affected by the floral-fruity aromas in these wines. The hotness results were exactly in line with the alcohol concentration of the wines, and the acetone perception results were in line with the volatile acidity data.

We chose 9 wines for a consumer hedonic study and found significant differences in liking with the wine highest in barnyard odor being by far the least liked. Additionally, the internal preference map showed that the Northern Californian consumers overwhelmingly rejected wines high in the barnyard attribute.

We conclude that price is not a major driver for the sensory attributes of Californian Petite Sirah wines.

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Chapter 1

Introduction

The purpose of this thesis research was to investigate commercially available California Petite Sirah wines and to understand the relationships among price, sensory and chemical attributes, and consumer preferences regarding these wines. The following literature review will indicate that Petite Sirah, also known as Durif, is underrepresented in research with only one published study (Patel and Shibamoto 2002) investigating this grape variety since UC Davis genetically identified Petite Sirah as Durif in 1999 (Meredith et al. 1999).

Literature Review

Durif, also known as Petite Sirah

The Petite Sirah red wine cultivar was isolated as a seedling from Peloursin vines by a French nursery worker, Francois Durif, in the late 19th century (Comiskey 2016). Petite Sirah, the progeny of Peloursin and Syrah, creates wines that are deeply colored and grippingly tannic, and it first arrived in the United States in 1884. Along the way, however, both in Europe and North America, there was much confusion regarding Petite Sirah's name and identity as Durif.

Previously, Petite Sirah was also used to refer to Syrah and many other field-blending varieties (Comiskey 2016). However, despite this confusion, it was a hero following California's phylloxera crisis, which devastated the California grape-growing and winemaking industries in the 1890s. Renowned for inky color, thousands of acres were planted pre-Prohibition. And later, with the rise of single-variety wines, Petite Sirah was soon high in demand.

The Petite Sirah-Durif entanglement did not unfold until Dr. Carole Meredith at UC Davis spearheaded genetic testing experiments to confirm the identity of Petite Sirah (Meredith et al. 1999). Despite this clarity, labeling laws commanded by the United States Tax and Trade Bureau distinguish between Durif and Petite Sirah wines to this day (Comiskey 2016).

Today, there are over 700 wineries in the United States that produce Petite Sirah wines (Comiskey 2016). The preliminary report for the 2022 California Grape Crush, created by the California Department of Food and Agriculture, reported over 87,000 tons of Petite Sirah grapes crushed in 2022 that were sold for a weighted average of $1,005.14 per ton. Meanwhile, approximately 43 tons of Durif were crushed in 2022 with an average weighted price per ton of $1,873.26.

Since the discovery of Petite Sirah's synonymy with Durif, some studies have been conducted with the grape variety, including research on the effects of various yeast strains on volatile production in Petite Sirah winemaking (Patel and Shibamoto 2002).

Descriptive Analysis

Descriptive analysis is a method that enables sensory scientists to holistically describe products by quantitatively measuring their various attributes and to subsequently differentiate among products using these attributes (Lawless and Heymann 2010). Descriptive analysis can be applied to a multitude of products, including beverages like wine (Canuti et al. 2020) or rum (Ickes and Cadwallader 2017) as well as products such as ice cream (Prindiville et al. 2000) or pet food (Koppel 2014).

Descriptive analysis panels typically include 8-12 judges that are trained via reference standards on the attributes of the product samples (Lawless and Heymann 2010). Following training, the panel evaluates the samples with replication. Throughout the entire experiment, product identities are hidden by three-digit codes. In addition, sample preparation and service are standardized for all panelists for the duration of the descriptive analysis experiment. Depending on the nature of the product, the number of samples served per session will vary (Heymann et al. 2014) . Highly astringent wines or spirits can be challenging or fatiguing for panelists, and generally no more than 6 samples are included per evaluation or training session.

During training, the panel is exposed to the full scope of products multiple times (Heymann et al. 2014). Throughout the training sessions, each judge first evaluates the product samples individually and silently, noting sensory attributes of each product and surveying the differences among product attributes. After judges individually evaluate each product, the group participates in a discussion led by the researcher serving as the panel leader. The panel leader asks each judge to list the product attributes they noted, and these attributes are then listed on the board for the entire group to view and discuss. The panel leader facilitates the discussion but does not contribute. The goal is to work toward a trained panel consensus of product attributes and their definitions. Following the listing of attributes, the panel leader attempts to create reference standards to help the panelists identify sensory attributes in the product samples. For example, if the product is wine, reference standards will typically be created for each wine's aroma, taste, and mouthfeel attributes. Reference standards can include a multitude of food-grade items, including spices, ingredients, or other products. After the panel leader creates the reference standards, the panel smells or tastes them and evaluates whether each reference standard aligns with what they sense in the product. Reference standard recipes are tweaked as needed to reach a panel consensus. Reference standard consensus enables a panel to calibrate their palates and ensure a uniform vocabulary during training before the evaluations (Heymann et al. 2014).

After training is completed, evaluations commence (Lawless and Heymann 2010). Before each evaluation session begins, judges smell and taste reference standards to help them remember the sensations of each attribute. Judges are individually isolated in a booth while evaluating the products. Evaluations include quantitative scales for each product and its attributes, ranging from 0-100 in intensity. Panelists interact with each product, whose identity is coded, in a balanced randomized order determined by a Williams Latin square or incomplete block design.

Following evaluations, descriptive analysis data is analyzed using programs such as XLSTAT or RStudio. Analysis often includes both univariate and multivariate statistical methods, including univariate analysis of variance (ANOVA), multivariate analysis of variance (MANOVA), and canonical variate analysis (CVA) (Lawless and Heymann 2010). These methods will be discussed in further detail later in this chapter.

Consumer Sensory Evaluation and Affective Testing

Consumer sensory evaluations are conducted to assess how much consumers like or dislike a certain product and to understand whether they prefer it over other products (Lawless and Heymann 2010). Contrasted with descriptive analysis studies, consumer sensory evaluations do not require panelists to undergo training to develop detailed understanding of the product, but they must be screened and determined as frequent users of the product to participate. Similar to descriptive analysis studies, product identities are hidden via random three-digit codes, so brand names are not included in evaluations. Consumers also receive products in balanced randomized orders to eliminate effects of serving order on the results.

To quantify consumer preferences, hedonic or affective test methods are often employed. The Quartermaster Food and Container Institute of the U.S. Armed Forces is credited with the development of a 9-point scale used to measure the degree of liking or disliking for a product (Peryam and Girardot 1952), as shown in Figure 1.1 below. The middle of the scale is neutral and represents indifference, the upper 4 points represent increasing levels of liking, and the lower 4 points represent increasing levels of disliking (Lawless and Heymann 2010). This hedonic scale allows consumers to operate non-analytically and to interpret the product experience holistically. With the variability of consumer liking and preferences, a larger sample size of 75–150 panelists is recommended. The nine-point hedonic scale has been employed for a plethora of tests since its development in the mid-1900's, including tests on milk (Su et al. 2022), olive oil (Delgado and Guinard 2010), mandarin oranges (Simons et al. 2018), and wine (Cliff et al. 2016). When conducting consumer studies such as these, a larger number of participants will increase accuracy (Delarue 2015).

Figure 1.1. Nine-point hedonic scale developed by U.S. Armed Forces Quartermaster Food and Container Institute (Peryam and Girardot 1952)

(9) Like extremely
(8) Like very much
(7) LIke moderately
(6) Like slightly
(5) Neither like nor dislike
(4) Dislike slightly
(3) Dislike moderately
(2) Dislike very much
(1) Dislike extremely

Statistical Analyses in Sensory Science

Univariate and Multivariate Analysis of Variance

One method to analyze sensory data is analysis of variance, which can be either multivariate (MANOVA) or univariate (ANOVA). Both ANOVA and MANOVA test for differences among treatments, and the primary difference is that ANOVA evaluates dependent variables individually while MANOVA evaluates all dependent variables simultaneously (Lawless and Heymann 2010). This analysis is useful to determine whether significant differences among treatments exist.

Typically, sensory data is analyzed first by a MANOVA then by individual ANOVAs to protect against statistical Type I error (Lawless and Heymann 2010). When a MANOVA is performed, the influence of all sensory descriptors is calculated simultaneously, and the result is an F-statistic based on Wilks' lambda. If Wilks' lambda is small and the F-statistic is significant, it can be concluded that samples differ significantly across the dependent variables or descriptors. If the Wilks' lambda is large and thus the F-statistic is not significant, the samples do not significantly differ across dependent variables. Individual ANOVAs are only performed if the MANOVA's F-statistic is significant, and F-ratios are computed for each ANOVA to determine significance of main or interaction effects. It is also important to note that MANOVA (but not ANOVA) accounts for collinearity, and correlations among descriptors are included via the covariance matrix in the F-statistic result of a MANOVA. As a result, performing the MANOVA first is an important statistical approach to sensory data, as seen in sensory science work involving green tea (Lee et al. 2008) and mead (Senn et al. 2021).

Canonical Variate Analysis

Canonical variate analysis (CVA) is also referred to as discriminant analysis (DA) and can be utilized to classify and separate products (Lawless and Heymann 2010). CVA depicts relationships among products in two-dimensional or three-dimensional graphs. Following the determination of significance for the main effect or interaction via MANOVA, CVA can be utilized to graphically visualize the mean separation among products. Canonical variate analysis has been used extensively in sensory science, including studies evaluating dairy products (Delarue and Sieffermann 2004) and marmalade (Mohammadi-Moghaddam and Firoozzare 2021).

Internal Preference Mapping

Internal preference mapping is a technique within sensory science used to graphically display hedonic data; the input is hedonic data, and the output is a product space with consumers as vectors (Lawless and Heymann 2010). The perceptual map portrays the relationships among products and individual consumers' liking of the products, and the entire map is based solely on consumer acceptance. With an emphasis on preference, the product positions in the map account for variations in the hedonic data. The first dimension of the internal preference map explains the maximum variability in preference directions among products. Typically, internal preference mapping is a principal component analysis (PCA) with products as samples and consumer liking scores as variables, and the goal is to identify two or three principal components that explain the maximum variation in consumer preferences. A minimum of six products that differ from one another should be used to achieve differences in consumer liking results, and all consumers should evaluate all products included in the study. Internal preference mapping is commonly adopted for a wide range of products, including cheese (Murray and Delhunty 2000) and wine (Biasoto et al. 2016).

Chemical Analysis

Standard Chemical Analyses

Chemical analysis is crucial to understand the composition of a wine. There are many standard chemical analyses utilized in the wine industry, including measuring a wine's pH, titratable acidity, residual sugar, ethanol, and volatile acidity (Iland et al. 2011).

A wine's pH is an equilibrium measure of the concentration of hydrogen ions in the wine (Boulton et al. 1996). It can be measured via a pH meter and an electrode. A typical wine pH resides between 3-4, with 3.3.-3.7 being most common for red wines (Waterhouse et al. 2016).

Titratable acidity (TA) is the concentration of titratable protons in a wine and is determined by measuring the concentration of strong base necessary during a titration to bring the wine to a specified pH endpoint (Waterhouse et al. 2016). TA includes both volatile and non-volatile acids and measures the sum of free hydrogen ions and weak organic acids in wine. It is often correlated with a wine's perceived sourness. It is also important to note that different countries employ different endpoints and acids in their titratable acidity measurements; for reference, in the United States, titratable acidity is expressed as tartaric acid and is measured using an endpoint of pH=8.2 (Boulton et al. 1996). In France and other European countries, titratable acidity involves an endpoint of pH=7.0 and sulfuric acid as the reference (Iland et al. 2012). Typical titratable acidity values thus differ according to the measurement parameters used for the specific titration. In the United States, a red wine's titratable acidity is usually between 5-8 grams per liter as tartaric acid (Waterhouse et al. 2016).

Residual sugar, or sugar remaining in a wine following alcoholic fermentation, is measured as the sum of its glucose and fructose content, the main fermentable sugars in wine (Iland et al. 2012). A wine's sugar content can be measured via multiple methods: Layne and Eynon, Rebelein, enzymatic, high-performance liquid chromatography (HPLC), reagent tablets, and reflectometry. A red wine that is considered "dry," or unsweet, will on average have 1-4 g/L concentration (Waterhouse et al. 2016).

Ethanol is the product of alcoholic fermentation; in alcoholic fermentation, yeast ferment sugars and produce ethanol and carbon dioxide (Waterhouse et al. 2016). A wine's ethanol content, or alcoholic strength, can be measured via hydrometry or ebulliometry (Iland et al. 2012). A typical dry table wine will possess between 11-14% ethanol (volume/volume) (Waterhouse et al. 2016). The percent volume of ethanol in a wine will vary slightly depending on the temperature at which the measurement is taken. Variations in temperature influence the density of ethanol, causing this difference in measurements (Iland et al. 2012). In addition, ethanol concentrations in wine will vary depending on the grape sugar concentration at the start of fermentation (Waterhouse et al. 2016). In warmer climates with longer growing seasons, grapes will have increased ripening. As a result, these wines tend to have higher ethanol concentrations than those produced in cooler climates with shorter growing seasons. In addition, red wine grapes are typically harvested later than white wine grapes and subsequently tend to produce wines with higher alcohol levels.

Volatile acidity (VA) in wine primarily refers to acetic acid, which is typically a result of bacterial spoilage at high concentration (Waterhouse et al. 2016). Limits vary by region or wine type but are generally between 1.0-1.5 g/L VA. Acetic acid has a pungent, vinegar-like aroma in isolation and is deemed volatile because it can be detected in a wine's sensory attributes. VA in wine is measured via distillation, which can occur in a Cash Still, Markham Still, or other specialized still (Iland et al. 2012). Following distillation, volatile acids are titrated with sodium hydroxide, and the concentration of volatile acidity is expressed as acetic acid.

WineXRay

As found on the WineXRay website (www.winexray.com), WineXRay is an analysis technique used to measure total anthocyanins (tANT), bound anthocyanins (bANT), free anthocyanins (fANT), (protein-precipitable) tannins (pTAN), and total (iron-reactive) phenolics (iRPs). It is an extended version of the Harbertson-Adams Assay, uses spectrophotometry in the ultraviolet-visible spectrum, and utilizes 17 different models to calculate outputs. The required equipment includes a centrifuge, sipper pump, spectrophotometer, and WineXRay software. WineXRay technology is utilized by various larger wineries throughout the United States, including Daou Vineyards, Far Niente Winery, and Larkmead Cellars, as found on the Wine Business website (www.winebusiness.com).

Anthocyanins are red-colored polyphenols that are found in red wines due to grapeskin contact with grape juice during the winemaking process (Waterhouse et al. 2016). Anthocyanins react with various compounds to produce red wine pigments, but with long-term age, pigments degrade. The pigmentation levels also depend on the pH and other wine additions. Measuring total anthocyanins in a wine is important to assess the color of the wine, and measuring free anthocyanins shows which anthocyanin form is presently reactive. Bound anthocyanins are another crucial measurement responsible for an aged red wine's color, and these products are formed by the reaction of tannin with anthocyanin.

Protein-precipitable tannins are tannins related to the organoleptic perception of wine, including the sensations of astringency and bitterness in red wine (Waterhouse et al. 2016). The foundation of the Harbertson-Adams assay is the precipitation of tannins using protein (Iland et al. 2012), and after precipitation, phenolic content of a wine can be measured (Waterhouse et al. 2016). This phenomenon is likely due to mimicking reactions that naturally occur between tannins in red wine and salivary proteins in the mouths of consumers.

Total (iron-reactive) phenolics, according to the WineXRay website (www.winexray.com), refers to gallic acid, caffeic acid, caftaric acid, tannins, and catechins. This measurement is used to understand extraction levels in red winemaking and does not include anthocyanins.

A typical total phenolic level for a red wine is 200 mg/L gallic acid equivalents, but this number can reach around 3500 mg/L in astringent, age-worthy red wines (Waterhouse et al. 2016). However, phenols in general, which does include all of the measurements in WineXRay's analysis, are typically present in red wine at an average level of 1550 mg/L in gallic acid equivalents (Waterhouse et al. 2016).

WineXRay measurements occur in parts per million in malvidin equivalents for total, free, and bound anthocyanin measurements and in parts per million catechin equivalents for protein-precipitable tannins and total (iron-reactive) phenolics.

WineXRay also provides spectrophotometric data for the three-dimensional CIEL*a*b* color space. The CIEL*a*b* color space approximates the Munsell space, and all three axes are perpendicular to one another (Lawless and Heymann 2010). The L* value indicates the lightness or whiteness; an increasing L* value means increasing lightness or whiteness. The a* and b* values together describe a point in space as Cartesian coordinates. The a* value represents red and green. A positive a* value indicates the color red; the more positive, the more red. A negative a* symbolizes the color green, and the more negative, the more green. Meanwhile, b* represents yellow and blue. Positive b* symbolizes the color yellow; the more positive, the more yellow. Negative b* values represent the color blue; the more negative, the more blue. The transmittance (T) measurement indicates how much light of a particular wavelength is transmitted rather than absorbed when a wine sample is run in the spectrophotometer in the ultraviolet-visible range (Iland et al. 2012). The I measurements reflect the light intensity, or how much of the light is absorbed when the spectrophotometer processes the wines.

Chapter 2[1]

Introduction and Literature Review

Petite Sirah, the progeny of the grapes Peloursin and Syrah, is a red grape variety first isolated by Francois Durif in the 19th century. It creates wines that are deeply colored and grippingly tannic (Comiskey 2016). It first arrived in the United States in 1884 and was the subject of much confusion regarding its identity. The Petite Sirah-Durif entanglement did not unfold until Dr. Carole Meredith at UC Davis spearheaded genetic testing experiments to confirm the identity of Petite Sirah (Meredith et al. 1999). However, labeling laws by the United States Tax and Trade Bureau (TTB) continue to distinguish between Durif and Petite Sirah wines to this day (Comiskey 2016).

Today, there are over 700 wineries in the United States that produce Petite Sirah wines (Comiskey 2016). The preliminary report for the 2022 California Grape Crush, created by the California Department of Food and Agriculture, reported over 87,000 tons of Petite Sirah grapes crushed in 2022 sold for a weighted average of $1,005.14 per ton. Meanwhile, approximately 43 tons of Durif were crushed in 2022 with an average weighted price per ton of $1,873.26.

Since the discovery of Petite Sirah's synonymy with Durif, some studies have been conducted with the grape variety, including research on the effects of various yeast strains on volatile production in Petite Sirah winemaking (Patel and Shibamoto 2002). However, Petite Sirah is underrepresented in academic research.

[1] This chapter is written as a manuscript for publication and will be submitted to the American Journal of Enology and Viticulture.

The purpose of this research was to bolster the understanding of Petite Sirah through the investigation of commercially available California Petite Sirah wines. To understand the relationship among price, sensory and chemical attributes, and consumer preferences in regard to these wines, a descriptive analysis, consumer study, and chemical analyses were performed.

Materials and Methods

Petite Sirah Wine Samples

Twenty-one California Petite Sirah wines were purchased (see Table 2.1), all from vintages 2017-2020 and from Lodi, Paso Robles, Napa Valley, Sonoma County, the Sierra Foothills, Mendocino, and California. Price ranges were High (H) at more than \$40 per 750 mL bottle (5 wines), Medium (M) at \$20-\$40 per bottle (9 wines), and Low (L) at less than \$20 a bottle (7 wines). All wines included in this study were from commercial producers.

Table 2.1. California Petite Sirah wine information and means of chemical and WineXRay analyses

			Chemical Means						WineXRay Means										
Wine Code	California Region	Price Range	Titratable Acidity (g/L)	pH	Glucose + Fructose (g/L)	Ethanol 60F (% vol)	Ethanol 20C (% vol)	Volatile Acidity (acetic, g/L)	tANT (ppm ME)	fANT (ppm ME)	bANT (ppm ME)	pTAN (ppm CE)	iRPs (ppm CE)	L*	a*	b*	I	T
A1	Paso Robles	$40-60	6.0	3.76	0.6	15.7	15.8	0.9	684.0	434.5	235.0	910.0	2006.0	51.1	44.4	6.7	0.4	0.6
A2	Napa Valley	$40-60	5.3	3.80	1.3	14.7	14.7	0.8	641.5	393.5	273.0	968.0	2064.0	52.7	41.9	11.3	0.4	0.7
B1	California	<$20	5.5	3.69	1.9	14.6	14.6	0.6	587.0	430.0	170.5	786.5	1939.5	63.9	34.4	4.8	0.3	0.7
B2	Paso Robles	$20-40	5.9	3.75	1.4	15.1	15.1	0.6	470.5	271.5	199.5	1046.5	2444.5	64.2	31.6	8.7	0.3	0.8
C1	Paso Robles	<$20	6.1	3.71	1.9	14.6	14.7	0.7	621.5	415.0	209.0	1156.0	2567.5	57.9	40.3	5.0	0.3	0.7
C2	Contra Costa County	<$20	6.0	3.75	6.3	14.1	14.1	0.7	472.0	318.5	157.0	725.0	1989.5	69.7	27.7	9.8	0.2	0.8
F1	Russian River Valley	$20-40	6.1	3.78	1.8	15.1	15.1	0.7	452.5	298.5	152.0	826.0	2026.5	70.4	27.8	6.6	0.2	0.8
I1	Lodi	<$20	6.1	3.59	5.5	13.1	13.2	0.5	515.5	344.0	161.0	1162.0	2641.0	65.1	34.6	2.6	0.3	0.7
J1	Paso Robles	$20-40	6.1	3.68	1.2	15.3	15.4	0.7	571.5	344.5	237.5	842.5	1964.0	55.5	41.5	12.0	0.4	0.7
L1	El Dorado	$20-40	6.1	3.65	0.5	16.0	16.1	0.7	436.5	256.5	174.0	999.5	2300.5	63.8	33.6	7.0	0.3	0.7
M1	Napa Valley	$40-60	6.6	3.71	0.8	16.7	16.7	1.2	574.5	315.5	281.0	656.0	1476.5	51.5	42.9	16.4	0.4	0.8
P1	Mendocino	<$20	5.6	3.66	1.0	15.0	15.0	0.7	561.0	329.0	224.5	1124.0	2381.0	54.5	41.5	5.7	0.4	0.7
P2	Dry Creek Valley	<$20	5.8	3.59	0.3	14.4	14.5	0.7	394.5	214.0	171.0	993.0	2249.0	63.1	35.1	6.7	0.3	0.7
P3	Dry Creek Valley	$20-40	6.5	3.39	0.6	15.4	15.4	0.7	750.5	534.0	210.0	1049.0	2278.0	50.6	49.7	5.0	0.4	0.6
R1	Dry Creek Valley	$40-60	5.3	3.64	0.7	14.1	14.2	0.6	387.5	213.0	154.0	1081.5	2498.0	64.6	34.2	3.9	0.3	0.7
S1	Paso Robles	$20-40	5.3	4.11	6.2	13.7	13.8	0.7	608.0	461.0	177.0	431.0	1401.5	70.4	21.9	9.1	0.2	1.0
S2	Lodi	<$20	6.4	3.52	0.9	15.1	15.1	0.8	673.5	488.0	203.5	705.5	1802.5	59.7	39.5	8.9	0.3	0.7
S3	Sonoma Valley	$20-40	6.0	3.76	0.1	13.3	13.3	0.7	340.0	130.5	179.0	920.5	2106.0	63.3	31.6	7.4	0.3	0.8
S4	Napa Valley	$20-40	6.0	3.56	1.1	14.8	14.9	0.7	518.5	307.5	216.5	987.5	2244.0	57.4	39.0	8.4	0.3	0.7
S5	Napa Valley	$40-60	6.0	3.58	1.1	14.9	14.9	0.7	674.5	495.5	194.5	757.0	1820.5	58.3	41.9	5.7	0.3	0.6
T1	Alexander Valley	$20-40	6.3	3.67	4.2	16.0	16.0	0.6	494.0	330.0	163.5	1026.0	2390.5	65.7	33.8	4.8	0.3	0.7

Descriptive Analysis

A descriptive analysis study was conducted at the J. Lohr Sensory Room at the Department of Viticulture and Enology at University of California, Davis. The panel included 10 judges (8 female, 2 male) recruited from students, staff, and friends of UC Davis based on availability and interest. The internal regulatory board (IRB) approved the protocol (IRB #1900329-1).

Descriptive Analysis Training

The panel leader trained participants during eight 60-minute sessions. In the initial training sessions, judges were exposed to a range of California Petite Sirah wines and asked to smell, taste, spit, and describe them. Descriptors and potential reference standards were generated. Next, the judges were presented with a subset of wine samples and reference standards each session until they arrived at a consensus regarding the wine attributes and reference standards. Reference standards were created by the panel leader from food and household products purchased from the supermarket. The panelists' training level was checked by quizzes throughout the training, where the panel was asked to identify reference standards for aroma, taste, and mouthfeel. By the end of training, panelists were exposed to all 21 wines in duplicate.

Descriptive Analysis Evaluations

The sensory profile of the California Petite Sirah wines included 29 attributes, all of which were anchored with reference standards and determined by panel consensus. There were 3 taste descriptors, 4 mouthfeel descriptors, and 22 aroma descriptors. The taste and mouthfeel attributes included sweet, sour, bitter, astringent, hot, puckering, and viscous. The aroma descriptors included the following: acetone, baking spice, barnyard, berry, black pepper, cherry, chocolate, cooked vegetables, dried fruits, earthy, ethanol, eucalyptus-mint, floral, grass, green bell pepper, herbal, jam, sherry, smoky, vanilla, white pepper, and woody. The recipes for the reference standards for these attributes are included in Table 2.2.

The wine samples were served in black wine glasses at room temperature with plastic lids. Every sample included 40 mL of wine. All wines were tasted blind and coded using randomized three-digit numbers. Before each evaluation session, judges smelled aroma reference standards and tasted the taste and mouthfeel standards to re-familiarize themselves with the attributes and panel consensus. Judges evaluated wines in isolated booths and utilized Compusense (https://compusense.com/) to input their evaluations. They ranked the attributes for each wine according to intensity from 0-100 on a line scale, with 0 representing “not present” and 100 representing “very intense.” Evaluations for each wine occurred in triplicate, over the course of 12 sessions, in a balanced randomized order. Judges were required to spit out all wine samples and wait at least one minute in between each wine. They were asked to clean their palates with water and unsalted crackers during each break. Following each session, panelists were provided with snacks. After the study concluded and a demographic questionnaire was completed by each judge, panelists were given a gift card for their participation. All descriptive analysis sessions were performed over the course of a month.

Table 2.2. Recipes for California Petite Sirah aroma, taste, and mouthfeel reference standards

Taste	Recipe	Product/Brand
Sweet	12 g/L cane sugar in distilled water	C&H™ pure cane sugar
Sour	2 g/L citric acid in distilled water	Millard™ citric acid

Bitter	100 µL/500 mL Isohop® in distilled water	Barth-Haas Group Isohop®
Mouthfeel		
Astringent	0.8 g/L alum in distilled water	McCormick® alum powder
Puckering	120 mL/L white vinegar in distilled water	Best Yet® 5% white distilled vinegar
Viscous	1 g/L carboxymethylcellulose (CMC) powder in distilled water	Sigma & Aldrich® food-grade CMC powder
Hot	250 mL/L Everclear® in distilled water	120-proof Everclear®
Aroma		
Acetone	1 drop from 3 mL pipette acetone on cotton ball	Klean-Strip® acetone
Baking spice	½ tsp mulling spices	Williams-Sonoma® mulling spice blend
Barnyard	Cow manure	From UC Davis cow barn
Berry	1 large/2 small raspberries + 1 large/2 small blackberries	Signature Select® frozen berries
Black pepper	⅛ tsp ground black pepper	Kirkland Signature™ coarse ground Malabar black pepper
Cherry	1 cherry + 1 tsp syrup	Fabbri Amarena cherries in syrup
Chocolate	½ piece chocolate (~2.5 g)	TCHO 66% bittersweet baking chocolate
Cooked vegetables	1 tsp canned asparagus juice + 1 tsp canned green beans juice	Signature Select® canned cut asparagus spears, Del Monte® canned green beans
Dried fruits	½ prune + ½ dried fig + 2 dried cherries + 6 raisins	Signature Select® pitted prunes, Sun-Maid® dried mission figs, Mariani® dried cherries, Signature Select® seedless raisins
Earthy	1 tbsp soil + 3 mL water + 1 tbsp chopped crimini mushroom	Miracle-Gro® potting mix soil, Signature Select® whole crimini mushrooms

Ethanol	20 mL Everclear®	120-proof Everclear®
Eucalyptus-mint	2 drops eucalyptus oil and 2 drops mint extract (3 mL pipette) on cotton ball	Aura Cacia® eucalyptus essential oil, McCormick® pure mint extract
Floral	2 mL rose water + pinch dried lavender	Sadaf® rose water, Spicely® organic dried lavender
Grass	1 tsp grass	Freshly cut lawn grass
Green bell pepper	1-inch x 1.5-inch piece freshly cut green bell pepper	Fresh green bell pepper from Safeway produce section
Herbal	1/2 dried bay leaf + 1 leaf fresh sage	Signature Select® dried bay leaves, O Organics® fresh sage
Jam	½ tsp mixed berry jam + ½ tsp red berry jam	Bonne Maman® mixed berries preserves, Mountain Fruit Co. "A Red Duet" strawberry and raspberry spread
Sherry	10 mL cream sherry	Harveys® Bristol cream sherry
Smoky	10 mL Scotch whisky	Laphroaig® 10-year Scotch whisky
Vanilla	15 drops (from 3 mL pipette) vanilla extract on ½ cotton ball	McCormick® pure vanilla extract
White pepper	⅛ tsp ground white pepper	McCormick® ground white pepper
Woody	1 tsp wood chips + 3 mL water + 8 1-cm strips cut leather shoelace	Nobile® fresh oak chips, Kiwi® outdoor leather shoelace

Consumer Evaluations

Based on a canonical variate analysis (CVA) of the descriptive analysis results, the nine most significantly different California Petite Sirah wines were selected for a hedonic study. Consumer evaluations were conducted at the J. Lohr Sensory Room at the Department of Viticulture and Enology at University of California, Davis, and spanned three days. There were 105 consumers recruited from students, staff, and friends of UC Davis based on availability and interest. The study did not include any of the descriptive analysis panel participants, and all consumers reported drinking red wine at least once per month. The internal regulatory board (IRB) approved the protocol (IRB #1900329-1).

The nine wine samples included in the consumer study were the following: S1, A2, B1, A1, J1, M1, C2, P2, and S3. Table 2.2 displays information regarding the wines' chemical analyses, regions, and price ranges. Wines were served in 20 mL portions in black wine glasses at room temperature with plastic lids. All wines were tasted blind, coded using randomized three-digit numbers, and served in a randomized order.

Judges were asked to smell, sip, and spit each wine and report how much they liked them on a nine-point hedonic scale, where 1 represents "dislike extremely" and 9 represents "like extremely." Consumers completed their evaluations in isolated booths and utilized Compusense to input their evaluations. In between each wine, they were required to wait one minute and asked to clean their palate with water and unsalted crackers. Following evaluations, consumers completed a wine knowledge questionnaire and a demographics questionnaire. At the end of the study, panelists were provided with snacks and awarded a gift card for their participation.

Chemical Analysis

Chemical analysis of all 21 wines was performed in duplicate by ETS Laboratories (www.etslabs.com). The chemical analysis included measurements of titratable acidity, pH, residual sugar (the sum of glucose and fructose), ethanol (at both 60 degrees Fahrenheit and at 20 degrees Celsius), and volatile acidity (as acetic acid). The means of these measurements are displayed in Table 2.1.

WineXRay Analysis

A WineXRay analysis (https://www.winexray.com/) was also performed for all 21 wines in duplicate. WineXRay is a technique used to measure total anthocyanins (tANT), bound anthocyanins (bANT), free anthocyanins (fANT), (protein-precipitable) tannins (pTAN), and total (iron-reactive) phenolics (iRPs). It is an extended version of the Harbertson-Adams Assay, runs spectrophotometry in the ultraviolet-visible spectrum, and utilizes 17 different models to calculate the outputs. The required equipment involves a centrifuge, sipper pump, spectrophotometer, and WineXRay software. The means of the duplicate WineXRay measurements are listed in Table 2.1.

Statistical Analysis

All data was collected via Compusense then analyzed using RStudio, Excel, and XLSTAT. Statistical analysis for the descriptive analysis study included univariate analysis of variance (ANOVA), multivariate analysis of variance (MANOVA), principal component analysis (PCA), multiple factor analysis (MFA), and canonical variate analysis (CVA).

The ANOVA and MANOVA were performed for price and for wine and their interactions with the other factors, including judge and replicate. For the MANOVA, Fisher's least significant difference (LSD) test was employed to distinguish among wines and their attributes. When wine as an effect was significant and involved in significant interactions among factors, a pseudo-mixed model was used and a new F-value was calculated to determine the significance.

The consumer evaluation data was analyzed using analysis of variance (ANOVA) and internal preference mapping. The chemistry and WineXRay data were analyzed using ANOVA. There were no missing data points for these datasets, and the significance level was always $p < 0.05$.

Results and Discussion

Chemical Analysis Results

The mean values for the chemical analyses of the 21 California Petite Sirah wines are listed in Table 2.1. The titratable acidity values fell within the range of 5.3-6.6 g/L, and pH values ranged from 3.39-4.11. These values are similar to many other dry red tables wines (Waterhouse et al. 2016). The residual sugar measurements indicated all of the wines were dry, ranging from 0.1-6.3 g/L glucose and fructose. The ethanol measurements (both at 60 degrees Fahrenheit and at 20 degrees Celsius) indicated all wines were relatively high in alcohol for dry red wines, with the lowest at 13.1% alcohol by volume (at 60 degrees Fahrenheit) for wine I1 and the highest alcohol by volume resting at 16.7% alcohol by volume (at both test temperatures) for wine M1. The measured alcohol for wine M1 contrasts with the listed 15.8% on the label. Volatile acidity measurements varied from 0.5 (wine I1) to 1.2 (wine M1) g/L acetic acid equivalents.

WineXRay Analysis Results

Table 2.1 also shows the mean values for the WineXRay measurements of the 21 California Petite Sirah wines included in this study. The measurements aligned with other tannic dry red table wines (Waterhouse et al. 2016). Total anthocyanin content ranged from 340.0-750.5 parts per million malvidin equivalents (ppm ME). Free anthocyanin content ranged from 130.5 ppm

ME (wine S3) to 534 ppm ME (wine P3). Wine S3 had the lowest total and free anthocyanin levels, and wine P3 had the highest total and free anthocyanin levels; thus, it can be concluded that wine S3 exhibited less red color compared to wine P3. Bound anthocyanin levels ranged from 152 ppm ME (wine F1) to 281 ppm ME (wine M1). Protein-precipitable tannins ranged in measurements from 431 parts per million catechin equivalents (wine S1) to 1162 ppm CE (wine I1). Iron-reactive phenolics measurements fell between 1401.5 ppm CE (wine S1) to 2641 ppm CE (wine I1). Wine S1 exhibited the lowest protein-precipitable tannin and iron-reactive phenolic measurements. This result aligns with how wine S1 had the least perceived astringency in the descriptive analysis, as seen in Table 2.3. Meanwhile, wine I1 has the highest levels of iron-reactive phenolics and protein-precipitable tannins. Wine I1 had a high perceived astringency, but the most (perceived-to-be) astringent wine in the descriptive analysis panel was wine P3, which potentially indicates interactive effects with other components on perceived astringency.

In addition to anthocyanin, tannin, and phenolic measurements, WineXRay also provides spectrophotometric data for the three-dimensional CIEL*a*b* color space. The L* value, which indicates lightness or whiteness (Lawless and Heymann 2010), ranged from 50.6 (wine P3) to 70.4 (wine S1). Wine P3 has the least whiteness, while wine S1 has the most whiteness. The a* and b* values work together as Cartesian coordinates with a* representing red and green and b* representing yellow and blue (Lawless and Heymann 2010). The a* values spanned from 21.9 (wine S1) to 49.7 (wine P3), while the b* values measured between 2.6 (wine I1) to 16.4 (wine M1). Because all a* and b* values were positive, the measurements represented the colors red and yellow respectively.

The intensity (I) measurements ranged between 0.2-0.4 with many wines tied for highest and lowest in intensity. The transmittance (T) values reached from 0.6 (wine P3) to 1.0 (wine S1). Wine P3, the wine with the least whiteness and the most total and free anthocyanins, allowed the least amount of light to be transmitted (more was absorbed). S1, the wine with the highest whiteness and the least total and free anthocyanins, allowed the most light to be transmitted (or the least light to be absorbed).

Table 2.3. California Petite Sirah descriptive analysis means with Fisher's least significant difference (LSD) for significant attributes

Wine Code	Acetone	Baking spice	Barnyard	Berry	Black Pepper	Cherry	Chocolate	Cooked Vegetables	Dried Fruits	Earthy	Ethanol	Eucalyptus-Mint	Floral	Grass	Green Bell Pepper	Herbal	Jam	Sherry	Smoky	Vanilla	White Pepper	Woody	Sweet	Sour	Bitter	Astringent	Hot	Puckering	Viscous
Wine A1	31.67	24.43	5.13	42.93	20.83	41.47	12.33	14.47	33.60	20.20	40.80	17.40	23.47	10.33	9.50	24.73	44.90	20.40	9.23	26.47	11.27	28.87	35.77	38.77	39.53	60.80	56.07	28.47	28.67
Wine A2	29.87	17.73	7.20	36.60	13.83	36.73	10.30	12.17	28.00	17.27	41.80	14.83	16.37	15.70	12.33	18.40	24.97	25.37	12.03	15.10	11.40	26.57	37.77	39.33	35.43	62.67	49.77	28.23	29.73
Wine B1	30.07	33.43	2.00	44.73	20.00	43.40	23.50	6.07	37.03	14.10	33.60	16.17	16.87	10.13	6.60	14.47	35.60	22.97	14.23	24.63	5.70	34.93	33.40	39.07	36.03	62.43	46.53	26.07	23.17
Wine B2	31.60	24.43	8.90	36.53	29.67	40.97	8.93	6.20	27.87	16.90	39.80	18.50	22.30	12.80	5.87	20.70	33.70	21.90	6.23	14.07	10.60	27.90	29.83	38.53	30.80	56.77	43.73	22.50	28.20
Wine C1	30.33	23.80	3.20	34.97	19.20	39.07	14.37	9.70	26.87	18.67	34.10	15.07	18.47	12.73	9.93	21.33	32.33	27.47	13.63	22.53	13.53	32.23	30.03	45.27	34.53	67.70	46.00	31.90	23.53
Wine C2	20.63	34.50	7.10	44.27	14.20	50.10	25.70	5.27	35.73	11.53	28.53	19.10	29.17	9.57	1.73	17.40	43.50	27.67	7.27	35.73	6.20	26.17	45.20	29.07	25.83	40.47	38.77	22.50	25.97
Wine F1	28.73	25.13	5.63	34.93	11.70	45.00	18.37	8.70	30.80	7.17	30.10	19.37	23.87	5.73	8.87	21.17	44.27	21.37	12.67	24.53	11.83	25.60	37.03	44.10	31.17	56.93	51.93	27.67	31.90
Wine I1	28.03	35.73	11.40	30.53	15.73	39.60	22.27	7.13	34.93	18.97	36.57	18.93	15.77	12.03	8.90	15.43	35.87	23.93	12.47	28.73	13.53	36.90	26.33	38.27	39.17	67.10	38.47	30.30	23.33
Wine J1	36.47	22.97	3.90	46.80	12.87	42.37	14.03	8.13	30.10	9.00	42.57	13.00	14.53	12.73	15.20	15.20	41.40	25.10	7.87	21.40	8.77	23.43	35.80	46.03	33.63	57.47	57.70	29.87	28.93
Wine L1	36.30	25.47	5.40	41.67	20.77	45.67	12.97	9.43	31.00	14.27	38.30	16.00	26.40	6.47	8.40	20.53	41.17	28.73	15.47	25.13	12.40	25.00	32.37	44.40	36.30	59.83	54.40	35.57	25.77
Wine M1	37.80	19.00	4.93	34.90	19.03	39.03	17.33	9.27	32.60	17.57	38.33	19.40	20.13	6.73	6.97	20.30	33.97	31.40	17.90	24.60	9.63	35.87	32.27	45.33	36.13	49.17	54.67	32.73	25.63
Wine P1	28.37	19.90	9.80	33.47	17.43	34.17	11.97	10.03	32.40	10.40	39.23	20.70	24.57	14.13	5.33	21.30	27.00	30.90	13.47	11.97	10.43	25.80	29.73	35.50	34.77	60.67	53.07	26.50	22.90
Wine P2	31.17	17.10	18.50	20.87	25.47	28.23	6.73	10.10	25.43	22.83	35.20	18.03	8.53	11.53	9.20	18.20	23.33	26.47	32.63	15.13	18.40	39.37	21.83	47.17	45.43	60.47	46.07	35.03	24.43
Wine P3	28.67	25.70	5.83	42.93	18.10	41.13	10.87	9.77	31.60	12.03	35.70	14.30	18.70	10.83	7.57	15.80	38.47	27.37	11.53	16.97	7.13	25.17	30.13	46.37	31.57	69.70	49.47	34.07	25.37
Wine R1	35.67	24.57	7.67	39.40	16.53	36.73	11.83	8.40	33.47	12.90	35.77	15.97	21.53	14.13	5.27	17.63	35.13	35.83	10.17	24.27	12.77	29.23	31.87	31.63	37.50	66.57	40.60	23.77	21.50
Wine S1	19.70	18.73	14.93	31.43	16.13	27.27	11.67	44.17	25.07	29.97	25.10	9.60	16.13	18.00	9.67	18.23	22.83	23.20	11.93	19.97	24.97	22.87	28.27	33.30	30.97	27.00	42.77	23.83	24.80
Wine S2	29.93	29.97	1.50	43.23	11.40	40.60	17.90	9.70	38.40	15.87	34.40	16.90	17.10	11.77	8.30	15.90	36.07	31.90	14.40	23.20	9.17	26.57	29.87	38.33	34.90	42.87	49.33	25.13	24.17
Wine S3	29.50	10.90	55.87	14.27	22.67	25.20	2.47	12.17	15.67	24.47	33.27	12.63	12.77	9.47	2.93	13.47	15.77	21.87	14.90	8.67	23.30	24.77	17.43	42.53	40.97	60.47	39.53	25.53	19.53
Wine S4	31.90	22.17	6.77	36.17	17.30	36.13	6.33	13.33	30.10	16.53	44.10	19.60	18.03	16.07	9.00	16.87	23.53	31.00	9.63	12.47	10.17	26.80	27.90	38.27	37.20	60.90	44.77	24.37	22.33
Wine S5	32.27	35.03	5.00	36.13	19.57	39.67	19.00	10.33	24.43	16.10	37.33	18.57	21.37	9.57	9.80	21.60	34.07	28.90	17.83	30.77	12.03	39.67	36.60	46.50	33.77	58.47	51.30	29.90	28.90
Wine T1	34.00	26.57	1.43	37.83	16.67	36.60	17.83	6.33	34.10	13.23	38.40	19.90	23.90	7.03	5.47	15.77	37.27	28.30	10.30	28.27	5.77	33.43	31.10	45.33	38.77	65.07	58.17	35.10	23.60
LSD	8.87	9.58	6.65	10.97	9.19	10.34	8.43	7.48		8.80	8.36						11.36		7.65	9.07	7.48	9.27	9.12	10.31		8.99	8.89		

Descriptive Analysis Results

Univariate and Multivariate Analysis of Variance for Price and Wine

Based on the analyses of variance performed on the descriptive analysis data, 19 attributes are significantly different among the California Petite Sirah wines. Table 2.3 shows these significantly different attributes, all of which have a calculated Fisher's least significant difference (LSD). The barnyard attribute had the lowest Fisher's LSD value at 6.65, while jam had the highest LSD at 11.36.

In general, most wines were quite similar with some noted differences. The exceptional wines tended to be very high in the following attributes: barnyard, cooked vegetable, earthy, and smoky. Price as an effect was only significant for three attributes, including the acetone attribute with the lower-priced wines having lower acetone scores; the sweetness attribute with higher-priced wines begin perceived as sweeter than the rest of the wines; and the hotness attribute with the higher-priced and medium-priced wines being perceived as hotter than lower-priced wines.

It is important to note that the sweetness perception result from the descriptive analysis was not supported by the residual sugar measurements (glucose and fructose concentrations) since lower-priced wines had significantly more glucose and fructose. One possible explanation for this discrepancy is that the perceived sweetness was affected by the floral and fruity aromas of these California Petite Sirah wines. The hotness results were exactly in line with the alcohol concentration of the wines, and the acetone perception results aligned with the volatile acidity measurements.

Figure 2.1. Principal component analysis (PCA) biplot showing 21 California Petite Sirah wines and their attributes evaluated in triplicate via descriptive analysis in the first two dimensions

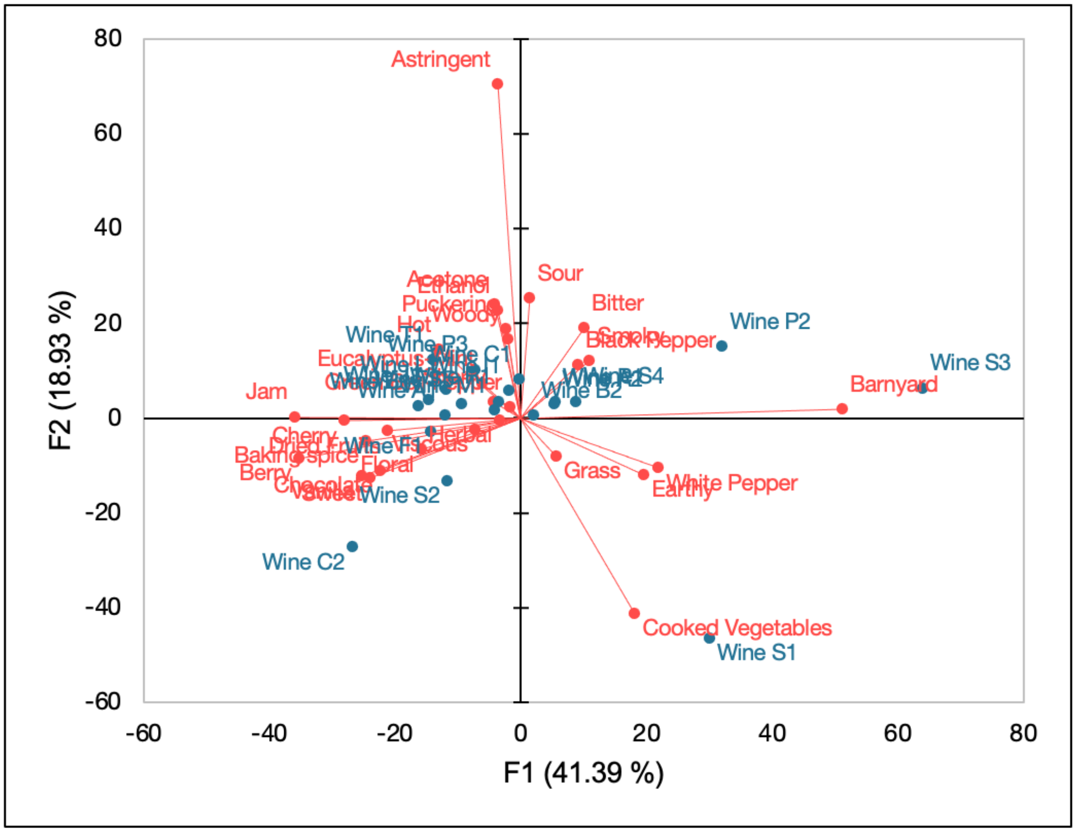

Figure 2.1 shows the principal component analysis (PCA) biplot of the 21 California Petite Sirah and their attributes evaluated in the descriptive analysis study. This biplot shows the first and second dimensions, which together explain 60.32% variability. The least liked wine in the consumer study, wine S3, is the most closely correlated with the barnyard attribute. Wine S1, the most liked by consumers, shows the highest correlation with the cooked vegetables attribute. It also had the lowest perceived astringency, as seen in Table 2.3.

Figure 2.2. Principal component analysis (PCA) biplot showing 21 California Petite Sirah wines and their attributes evaluated in triplicate via descriptive analysis in first and third dimensions

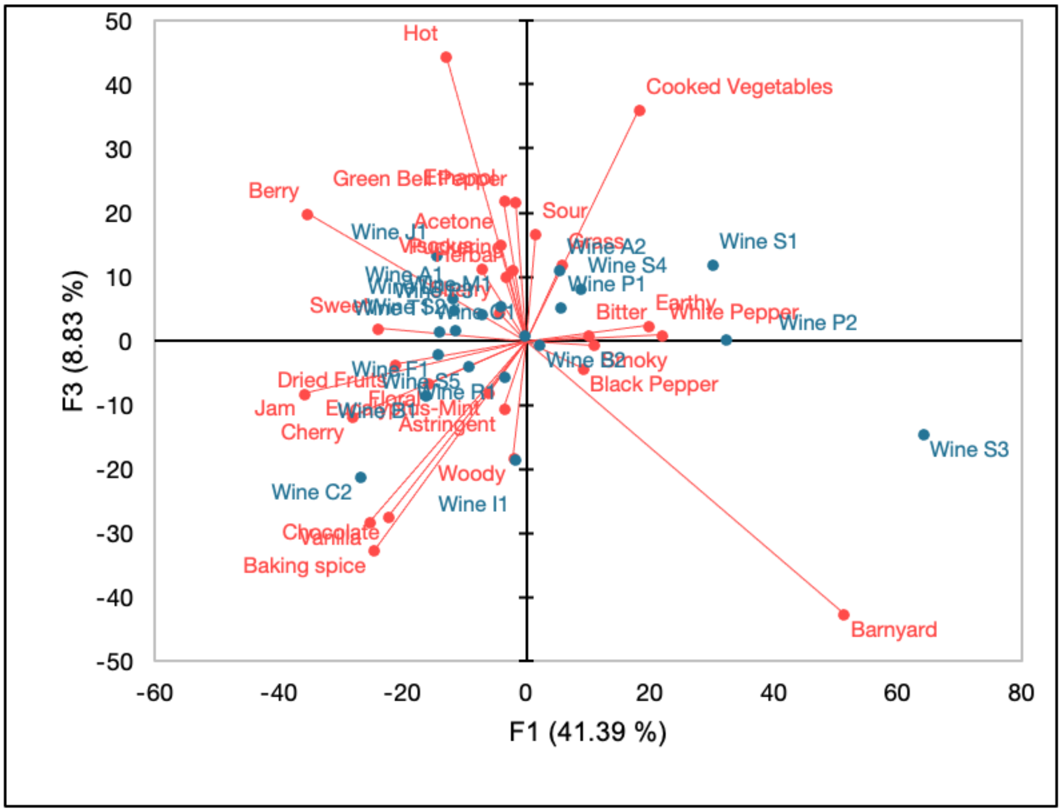

Figure 2.2 shows the principal component analysis (PCA) biplot of the 21 California Petite Sirah and their attributes in the first and third dimensions. These dimensions together explain 50.22% variability. Wine S3 is a marked outlier from the rest of the wines, showing the highest correlation with the barnyard attribute. The barnyard attribute also has a high negative correlation with the berry attribute.

Figure 2.3. Canonical variate analysis (CVA) plot of 21 California Petite Sirah wines evaluated in triplicate in descriptive analysis in the first two dimensions

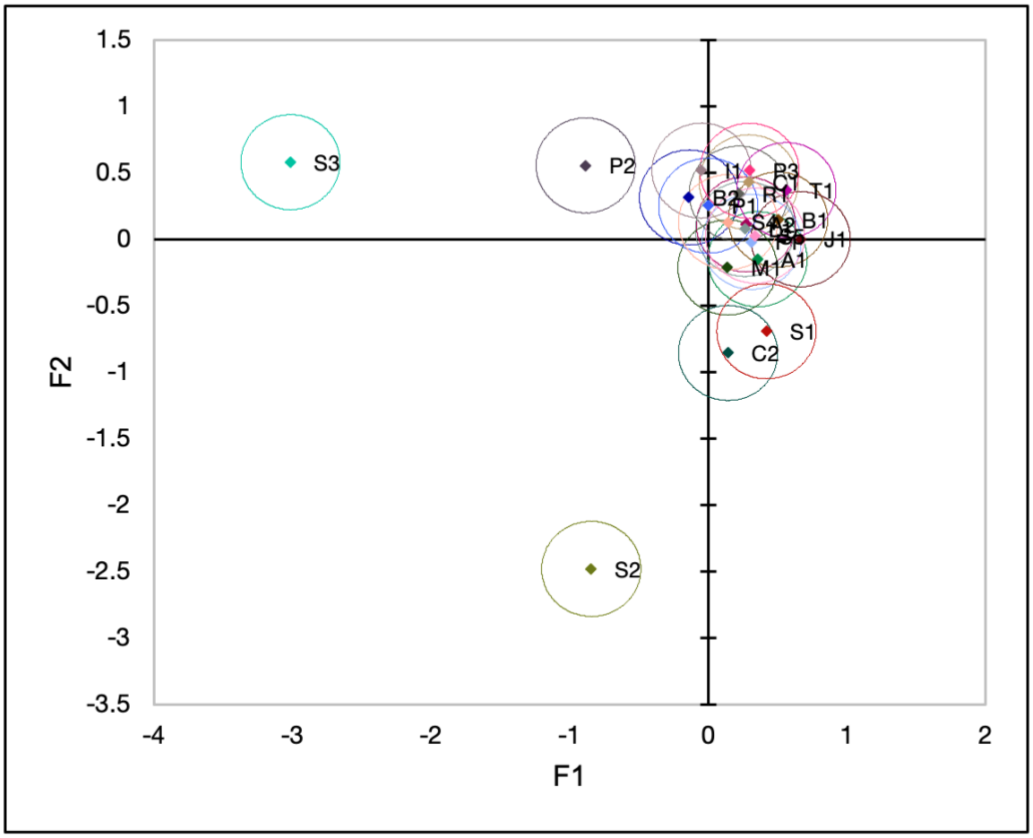

Figure 2.3 shows the canonical variate analysis (CVA) plot of 21 California Petite Sirah wines. The most liked wine (S1) and least liked wine (S3) from the consumer study are significantly different from the rest of the wines, which are clustered more closely together.

Figure 2.4. Attributes plot from canonical variate analysis (CVA) plot of 21 California Petite Sirah wines evaluated in triplicate in descriptive analysis in first two dimensions

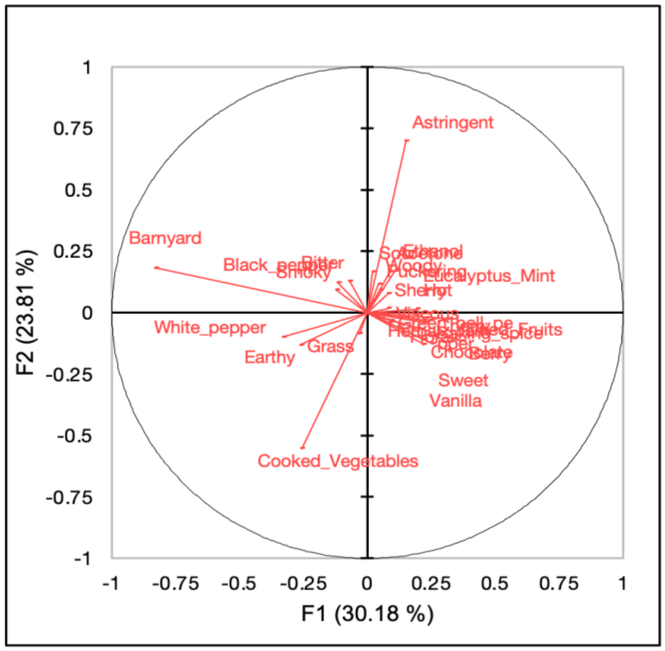

Figure 2.4 shows the attributes plot from the canonical variate analysis (CVA) of 21 California Petite Sirah wines evaluated in triplicate in descriptive analysis. The first two dimensions together explain 53.99% variability. There is a close clustering of attributes toward the center of the plot with some notable exceptions, including the barnyard, cooked vegetables, and astringent attributes projecting further outward.

Consumer Evaluation Results and Internal Preference Mapping of Wines

Out of the 21 wines included in the descriptive analysis study, the 9 most significantly different wines (determined via CVA) were chosen for a consumer hedonic study. There were significant differences found in liking, and the California Petite Sirah wine with the highest barnyard odor

(Wine S3) was by far the least liked. Additionally, the internal preference map showed that the Californian wine consumers overwhelmingly rejected wines high in the barnyard attribute.

Table 2.4. Average liking of 9 California Petite Sirah wines by 105 red wine consumers on a 9-point hedonic scale

Wine	Liking
S1	6.01
A2	5.92
B1	5.91
A1	5.67
J1	5.46
M1	5.37
C2	5.26
P2	5.06
S3	3.27
LSD	0.551

Figure 2.5. Internal preference mapping biplots from hedonic study with 105 red wine consumers and 9 California Petite Sirah wines in (A) 1st and 2nd and (B) 1st and 3rd dimensions

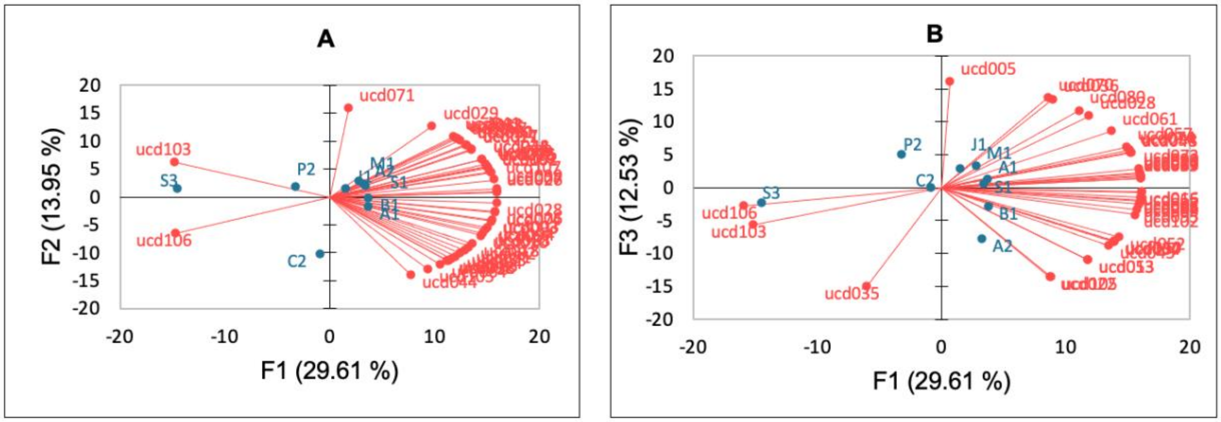

Table 2.4 shows the average liking scores for the 9 California Petite Sirah wines included in the hedonic testing. The scale ranged from 1-9, with 1 representing "dislike extremely" and 9 representing "like extremely." Wine S1 was most liked by consumers and had an average liking of 6.01 out of 9. Wine A2 and B1 followed closely behind, with average hedonic scores of 5.92 and 5.91 respectively.

Figure 2.5 shows the internal preference maps for California Petite Sirah wines tasted by 105 Northern California red wine consumers. Biplot A is positioned in the first two dimensions, which explain 43.56% of variance. Biplot B shows the first and third dimensions, which together explain 42.15% variance in consumer preference. Both biplots indicate that the Californian red wine consumers overwhelmingly rejected wine S3, which was high in the barnyard attribute, according to the descriptive analysis panel (Table 2.3). Wine P2, the second least-liked wine, was also high in barnyard aromas.

As seen in the data in Table 2.3, wine S1, the most liked wine by red wine consumers, had the lowest perceived astringency according to the descriptive analysis panelists (which was corroborated by the low levels of protein-precipitable tannins, as measured by WineXRay). This wine also had the lowest rating for the acetone, ethanol, baking spice, and sweet attributes by the descriptive analysis panel, all of which were significant attributes according to the ANOVA. Wine S1 also had the highest level of the following significant attributes: cooked vegetables, earthy, woody, and white pepper. The author speculates that the liking derives from the lowest perceived astringency of wine S1.

Conclusion

This work has characterized the sensory and chemical attributes of California Petite Sirah wines and consumers' perceptions of these wines. The statistical analysis indicated that price is not a major driver for the sensory attributes of Californian Petite Sirah wines. In addition, consumers did not prefer California Petite Sirah wines with the barnyard attribute. Rather, red wine consumers most preferred the Petite Sirah wine with the lowest perceived astringency, the highest levels of cooked vegetables, earthy, woody, and white pepper attributes, and the lowest levels of acetone, ethanol, baking spice, and sweet attributes, as rated in the descriptive analysis.

Chapter 3

Conclusion

This work investigated commercially available California Petite Sirah wines. A literature review indicated that Petite Sirah, also known as Durif, is underrepresented in research with only one published study investigating this cultivar since UC Davis genetically identified Petite Sirah as Durif (Meredith et al. 1999). A sensory panel (n=10) evaluated 21 California Petite Sirah wines with varied price points and regionalities to construct a lexicon of 29 terms to describe the wines' aroma, taste, and mouthfeel characteristics. The significantly different wines were the basis of the hedonic evaluations, during which 105 consumers rated 9 California Petite Sirah wines based on levels of liking. Chemical and WineXRay analyses were performed to further understand the composition of these wines.

The results indicated that price is not a major driver for the sensory attributes of California Petite Sirah wines. In addition, consumers did not prefer wines with the barnyard attribute. Rather, red wine consumers most preferred the Petite Sirah wine with the lowest perceived astringency, the highest levels of cooked vegetables, earthy, woody, and white pepper attributes, and the lowest levels of acetone, ethanol, baking spice, and sweet attributes, as rated by the descriptive analysis panel. It was speculated by the author that the low perceived astringency was a significant driver for consumer preference of this notoriously tannic (Comiskey 2016) grape variety.

The work presented in this thesis is a step toward understanding Petite Sirah chemically, sensorily, and hedonically. The outcomes warrant future research to differentiate Petite Sirah wines produced in various parts of the world and continuing to understand consumer preferences. Petite Sirah is used frequently as a blending grape, as detailed by *Wine Enthusiast* (www.winemag.com), but could fill a gap in the market where other red wines are declining in growth and losing market capitalization. In 2022 red wine blends exhibited a growth rate of -11.2%, while Cabernet Sauvignon varietal wines experienced a -4.7% growth rate (McMillan 2023). The author speculates that with further research and understanding of consumer preferences of Petite Sirah, especially in how it compares to wines produced with other red grape varieties, there is potential to increase Petite Sirah's growth rate as a varietal wine and to diversify wine offerings, especially in California.

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Appendix A

Figure A.1. Multiple factor analysis (MFA) to compare 10 trained judges in descriptive analysis study of California Petite Sirah wines

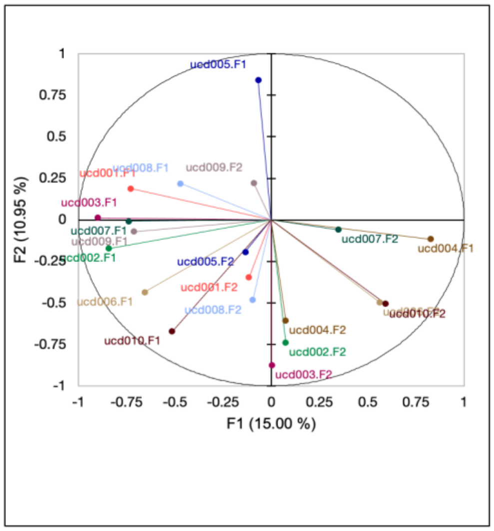

Figure A.1 depicts the multiple factor analysis (MFA) used to compare the 10 panelists in the descriptive analysis study of California Petite Sirah wines. In general, the panelists were clustered closely together across the first and second dimensions with the exception of the fifth panelist in the first dimension.