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What Consumers Are Looking for in Strawberries: Implications from Market Segmentation Analysis

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ABSTRACT

An online choice experiment was conducted to investigate U.S. consumer preferences for attributes of fresh market strawberry fruit. Using a latent class logit model, three different groups of consumers are identified: "Balanced Consumers," "Experience Attribute Sensitive Consumers," and "Search Attribute Sensitive Consumers." This information on consumer segmentation can help the fresh market strawberry industry identify target markets, and provides valuable information to breeders, growers, and retailers to prioritize fruit attributes in their breeding, growing, or product sourcing decisions. © 2016 Wiley Periodicals, Inc.

1. INTRODUCTION

Strawberry is a fruit with steadily increasing consumer demand and year-round product availability provided by multiple production locations around the globe. The United States is currently the world's largest strawberry producer, accounting for over 28% of total production (Wu et al., 2012). From 2000 to 2014, annual U.S. strawberry production averaged 1.1 million metric tons and had a farm gate value of $1.8 billion (USDA, 2015). Thousands of strawberry cultivars are available and since 2007 more than a hundred new cultivars have been released in the United States (U.S. Department of Commerce, Patent and Trademark Office, 2015). The development of new cultivars (Alpuerto, Norton, Alwang, & Ismail, 2009; Luby & Shaw, 2000) requires substantial knowledge and resources. Systematic identification of fresh fruit attributes consumers prefer can help breeders and growers focus on developing and producing strawberry cultivars that appeal to consumers, thereby increasing marketplace success and improving the sustainability of the industry.

Many previous studies have focused on consumer preferences for fruit attributes and some of these studies employed choice experiments (Carroll, Bernard, & Pesek Jr, 2013; Onken, Bernard, & Pesek Jr, 2011; Shi, House, & Gao, 2011; Yue & Tong, 2011; Zhang, Gallardo, McCluskey, & Kupferman, 2010). Only a few of these studies focused on fresh market strawberry attributes and most were conducted at a state or regional level in the United States or in foreign countries. Results from Safley et al. (1999) indicated that freshness is the most important attribute for strawberry consumers in North Carolina, followed by taste, firmness, color, and berry size. Colquhoun et al. (2012) found that sweetness and complex flavors are the most important

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attributes for U.S. strawberry consumers. In their sensory tests, Ford et al. (1996) found that Australian consumers consider flavor, sweetness, and juiciness as the most important attributes. Similarly, Keutgen and Pawelzik (2007) found that sugar content, especially sucrose, is the most important factor. Lado et al. (2010) reported that consumers in Uruguay prefer sweeter and firmer fruit.

Consumer preferences are not homogeneous. Existing literature suggests that various consumer segments may value products differently (Boxall & Adamowicz, 2002; Teratanavat & Hooker, 2006). For example, consumers' preferences for sweet cherry attributes vary across different groups of consumers (Zheng et al., 2016). Ideally, breeders and producers should be able to develop and produce strawberries that can satisfy each individual consumer's unique need and preference. But this level of segmentation is impractical for the strawberry industry because strawberries are mass-produced and development of new strawberry cultivars requires extensive time, human capital, and financial capital inputs. One approach to balance the efficiency of mass-marketing (by supplying all strawberry consumers with similar quality attributes) with the effectiveness of customized marketing (by offering each individual consumer exactly what she or he wants) is to divide the market into manageable number of segments. Then breeders and growers can develop and grow different varieties of strawberries to satisfy each segment's preferences. Previous studies examining consumer heterogeneity and marketing segmentation for different products have used consumer-specific characteristics such as demographic and geographic information, as well as attitudes and purchasing habits, to distinguish groups (James et al., 2009; Rigby & Burton, 2005; Teratanavat & Hooker, 2006; Thach & Olsen, 2006). Others identified consumer segments based on consumer preferences for product attributes. For instance, Ortega et al. (2011) analyzed Chinese pork consumers' preferences for food safety information and, based on heterogeneous consumer preferences, identified four classes of consumers: "Price Conscious"(38%), "Certification Conscious"(13%), "Pork Lovers" (28%) and "Worried Consumers"(21%). The willingness to pay (WTP) values for traceablity and government or private certifications and labels differ among these four classes. Sociodemographic variables and the risk perception of food safety were important factors explaining preference heterogeneity. Panico et al. (2014) showed that certification and origin labels significantly affect consumer preferences for Italian extra-virgin olive oil, and identified four consumer segments, namely, "Indifferent to advanced certification"(40%), "Attentive to local origin"(30%), "Sensitive to certification"(20%), and "Strongly oriented towards certification and attentive to labeling"(10%). These groups are not differentiated by consumer sociodemographics such as gender, age, and income, but rather by health perception, purchasing frequency of olive oil and the frequency of direct purchases from farmers. Zheng et al. (2016) investigated consumer preferences for sweet cherry attributes and identified four consumer groups: "Flavor Sensitive Consumers" (36%) "Price Sensitive Consumers" (26%) and "Storage Sensitive Consumers"(38%). Sociodemographic characteristics, such as age, income, race, and number of children at the household characterize the different segments.

To our knowledge, the only consumer segmentation study on strawberries was conducted by Januszewska et al. (2006), for fresh market strawberries in the Philippines. Using cluster analysis, they found three groups of consumers: "Balanced Consumers," "Critical Consumers," and "Positive Consumers." Consumer characteristics such as the complexity of their experience, attitude toward fresh strawberry consumption, expectation of strawberry tastes as well as place of purchase, but not demographics, differ across segments. Our study contributes to the literature on segmentation of U.S. consumers' preferences for strawberry attributes and addresses the following questions: Are there consumer segments in terms of preferences for strawberry attributes? If so, which consumer groups can we identify? What are the variations in the preferences across different groups of strawberry consumers? What are the characteristics for each group of consumers? What marketing strategies should be adopted for each of these consumer groups? To answer these questions, we conducted a choice experiment using online surveys and employed a latent class logit model to identify different segments of U.S. fresh market strawberry fruit consumers.

The remainder of this article consists of three sections. The next section describes our materials and methods. The following results section summarizes the data and the results from the data analysis. The final section presents the conclusions and marketing implications.

2. MATERIALS AND METHODS

2.1 Choice Experiment

Lancaster (1966) extended traditional demand theory by focusing on the attributes of a market good, and not the market good itself. In particular, the theory developed by Lancaster implies that the overall utility of a good can be decomposed into separate utilities for each attribute of the good. Choice experiments are useful for data collection when there is an interest in product attributes, and have been widely used in studies on consumer preferences, WTP, and consumer segmentations (Carroll et al., 2013; Hoke et al., 2014; James et al., 2009; Onken et al., 2011; Shi et al., 2011; Yue & Tong, 2009; Zhang et al., 2010). Choice experiments present participants with options consisting of different combinations of attribute levels and participants are asked to choose between the options. The levels of the attributes vary among the alternatives such that choice experiments replicate consumers' rational decision-making process and can be used to derive the utilities for different attributes. Moreover, a cost attribute is included in each choice set, which enables researchers to convert the marginal utilities into marginal valuations for each attribute. Choice experiments have been under scrutiny as they do not control for the possibility of hypothetical biases, as participants do not face consequences for the choices they make. That is, since participants do not pay "real money" when making decisions, their choices are considered hypothetical. Nonetheless there are several studies supporting the validity of choice experiment findings. Carlsson and Martinsson (2001) suggested that choice experiment responses are statistically indistinguishable across hypothetical and nonhypothetical (real purchasing) treatments. Lusk & Schroeder (2004) demonstrated that the bias associated with estimated marginal WTP using hypothetical choice experiments is reduced when choice experiments frame questions in a way that is similar to actual purchasing settings. By comparing the hypothetical and nonhypothetical experiment, Yue & Tong (2009) also found that the hypothetical bias (the difference between the actual WTP and what participants say they are willing to pay) is not statistically significant different from zero.

In our study, choice experiments were used to elicit consumers' preferences for six attributes of fresh market strawberry fruit. The choice experiment consisted of eight scenarios, each comprising two unique combinations of strawberry traits and costs. Each scenario was presented separately and participants chose the preferred of the two options. To mimic actual purchase settings, an opt-out option was also included, enabling participants to choose neither of the two options. In addition to the eight choice scenarios, we also asked nineteen questions about participants' sociodemographic backgrounds and strawberry purchasing habits.

Based on previous studies, consultation with industry experts, and focus group discussions with consumers, six strawberry attributes and attribute levels were identified for use in the choice scenarios: external color, size, internal color, firmness, flavor, and shelf life (Table 1). We also included two price levels, \$2.99/lb and \$2.65/lb. To help consumers visualize the strawberries, we used pictures for attributes such as external color, size and internal color, as shown in Figure 1.

The choice experiment was conducted online, using Qualtrics ™ a professional survey company. The nationwide panel of participants were randomly selected and recruited by Qualtrics ™. Only participants who had purchased strawberries in the past year were invited to participate.

2.2 Econometric Models

The random utility model is a fundamental approach in econometric analysis of choice behaviors. The random utility approach is based on the premise that the utility derived from purchasing or consuming a good is comprised of a deterministic component (from the

TABLE 1. Strawberry Attributes and Attribute Levels Used in the Choice Experiments

Attributes	Attribute Levels
External color	Ideal red color
	Too light or too dark color
Size	Larger than a quarter (large)
	Almost same as a quarter (small)
Internal color	Ideal red color
	Too light or too dark color
Firmness	Firm
	Soft
Flavor	Intense strawberry flavor
	Mild strawberry flavor
Shelf-life	9 days at home in refrigerator
	4 days at home in refrigerator
Price	2.99/lb
	2.65/lb

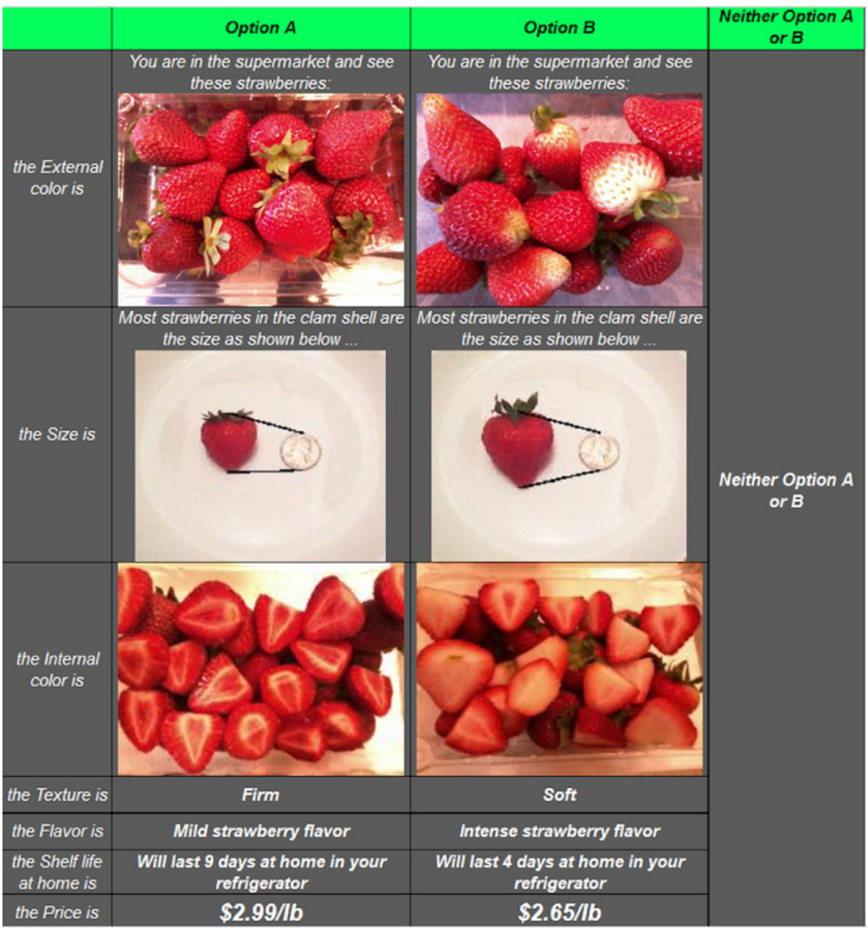

Figure 1 An Example of Choice Scenarios in the Choice Experiment.

observable characteristics) and a stochastic (error) component. The basic premise is that choice decisions are made based on different product attributes among alternatives (McFadden 1986; 2001). Different discrete models can account for unobservable preference heterogeneity. For example, the mixed logit model accounts for preference heterogeneity by allowing parameters to vary randomly, but it is not well suited to explaining the sources of heterogeneity (Boxall & Adamowicz, 2002). Several researchers (Greene & Hensher, 2003; Hess et al., 2011) found evidence that the latent class logit model has some advantages in market segmentation analysis. As a semiparametric specification, the latent class logit model does not rely on strong distributional assumptions about individual heterogeneity. Furthermore, the heterogeneity in preferences across individuals in conjunction with heterogeneity in external variables (covariates) can be accommodated by the latent class logit model. By linking the class allocation to individual-specific variables, the latent class logit model is able to assess richer heterogeneity patterns simultaneously with the identification of segments. The latent class logit model relies on a finite distribution structure, which is less likely to suffer from computational and interpretational issues compared to continuous mixture models such as the mixed logit model (Hess et al., 2011).

In the latent class model, it is assumed that individuals are sorted into L classes and consumers have distinctive taste parameters across the classes, $\alpha = (\alpha_1, \ldots, \alpha_L)$. That is, consumer preferences are assumed to be heterogeneous across classes but homogeneous within a class (Boxall & Adamowicz, 2002). The latent class logit model is generally specified with an underlying logit model, and the probability that an individual n chooses option i ($i = 1, \ldots, M$) in choice scenario t ($t = 1, \ldots, T$) is:

$$\Pr(x_{nit}|l) = \frac{\exp(a_l x_{nit})}{\sum_{j=1}^{M} \exp(a_l x_{njt})} \tag{1}$$

where x_{nit} is a vector of observed attributes associated with individual n who chooses option i in scenario t, and α is a vector of class-specific utility parameters.

Let y_{nit} denote a binary variable which equals 1 if individual n chooses alternative i in scenario t and 0 otherwise. For a given class assignment, l, the probability of individual making a sequence of choices would be the joint probability:

$$\mathrm{P_n}(l) = \prod_{t=1}^{T} \prod_{i=1}^{\mathrm{M}} \left(\frac{\exp\left(a_l x_{nit}\right)}{\sum_{j=1}^{M} \exp(a_l x_{njt})} \right)^{y_{nit}} \tag{2}$$

Since the status of class membership is unknown and to be determined as part of the modeling process, the weight for latent class l is the population share of that class and specified by the fractional multinomial logit. Let $\pi_{nl}(\theta)$ denote the probability individual n falls into class l:

$$\pi_{nl}(\theta) = \frac{\exp(\theta_l z_n)}{1 + \sum_{k=1}^{L-1} \exp(\theta_k z_n)} \tag{3}$$

where z_n is a set of observable characteristics for individual n, and $\theta = (\theta_1, \theta_2, \ldots, \theta_{L-1})$ is the vector of membership parameters (Pacifico & Yoo, 2012). The log likelihood function for the sample can be obtained by summing each individual's log likelihood:

$$\ln L = \sum_{n=1}^{N} \ln \sum_{l=1}^{L} \pi_{nl}(\theta)\, P_n(l) \tag{4}$$

With the coefficients estimated from latent class logit model, the posterior estimate of the probability that individual n belongs to latent class l evaluated at the s^{th} iteration estimates can be calculated based on Bayes theorem (Greene & Hensher, 2003):

$$\hat{H}_{nl}(\theta^s) = \frac{\hat{P}_n(l)\,\hat{\pi}_{nl}(\theta^s)}{\sum_{k=1}^{L}\hat{P}_n(k)\,\hat{\pi}_{nk}(\theta^s)} \tag{5}$$

3. RESULTS

3.1 Summary Statistics

The summary statistics for consumers' sociodemographic backgrounds and strawberry purchasing and eating habits are listed in Table 2. About 1200 people participated in the online choice experiment and 1062 participants completed the survey. Participants' average age group is 35 to 44 years old. Thirty-three percent are male, 76% are Caucasians, and the average education level is a 2-year college or technical degree. Forty-six percent of the respondents have one or more children under 18 years old in the household. Thirty-six percent live in the South and 23% in the Midwest, followed by 19% in the West and 14% in the Northeast. On average, there are two to three people in each household, and the average annual household income is between \$35,000 and \$49,999. The demographic background for the sample is very similar to the U.S. census data (U.S. Department of Commerce, Census Bureau, 2014) except that our sample has a relatively higher proportion of female.

Forty-five percent of the participants indicate that they eat fresh strawberries less than 2–3 times a month, and more than half eat strawberries more frequently. Most participants purchase strawberries in conventional grocery stores and from warehouse retailers, followed by farmers' markets, natural food stores, food cooperatives, and direct sales. The labels on strawberries at point of sale also influence consumers' decisions: around 77% of the participants think safety-related information on labels is important; more than 40% of the participants consider health-related information on labels and the organic logo as important; and around 30% regard eco-, local-, and sustainable-grown labels as influential factors. Non-GMO and brand labels are relatively unimportant for strawberry purchases. A Non-GMO label is considered as important for only 22% of participants and a private brand label is important for 14% of participants.

3.2 Consumers Segmentation-Latent Class Logit Estimation Results

In empirical studies, information criteria such as Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), consistent Akaike Information Criterion (CAIC), and Posterior Prediction Accuracy are frequently used when choosing the optimal number of latent classes (Boxall & Adamowicz, 2002; Pacifico & Yoo, 2012). As shown in Table 3, for the latent class models estimated in this study the BIC and CAIC are decreasing as the number of latent classes increases, indicating that models with more latent classes fit the data better. However, the posterior prediction accuracy is declining as the model includes more classes. Combining these criteria, we find the model with three classes optimally distinguishes subgroups: the BIC, AIC, and CAIC decrease to a large extent without much sacrifice of the posterior prediction accuracy.

The estimation results of the latent class logit model using three classes are presented in Table 4. Particiants in Group 1 are labeled *Balanced Consumers*, and account for 65.6% of participants in the sample. This group is "balanced" because the coefficients of all attributes are significant, indicating participants care about all of the strawberry traits, although the trait coefficients are not the highest in magnitude among the three classes or segments. These participants tend to choose strawberry fruit with a lower price, ideal red external and internal colors, intense strawberry flavor, longer shelf life, and firm texture. The coefficient for size is the lowest among the three groups, but it is still significant at the 5% level. Compared to the other

TABLE 2. Summary Statistics of Survey Participants (N = 1,062)

Variables	Description of Variables	Mean (SD)	U.S. Census
Age	The age of participant	3.10 (1.56)	3.22
	1 = 18–24 years old	17.23%	
	2 = 25–34 years old	26.37%	
	3 = 35–44 years old	16.85%	
	4 = 45–54 years old	16.48%	
	5 = 55–64 years old	15.25%	
	6 = 65+ years old	7.82%	
Male	1 if male; 0 if female	0.33 (0.47)	0.49
Education	The highest level of education	3.04 (1.06)	3.39
	1 = Some high school or less	3.02%	
	2 = High school diploma	34.31%	
	3 = 2 year college or technical/other degree	29.31%	
	4 = 4 year college degree	22.62%	
	5 = Advanced college degree	10.74%	
Caucasian	1 if Caucasian; 0 otherwise	0.76 (0.43)	0.74
Income	Household annual income before taxes	3.25 (1.65)	3.05
	1 = Less than $25,000	19.79%	
	2 = $25,000–$34,999	17.62%	
	3 = $35,000–$49,999	17.06%	
	4 = $50,000–$74,999	21.30%	
	5 = $75,000–$99,999	11.59%	
	7 = $100,000 or more	12.63%	
Children	1 if participants have one and more children under 18 years old in the household; 0 otherwise	0.46 (0.50)	–
Household Size	Number of people in the household	2.72 (1.24)	–
State	1 if participants live in northeast	0.14 (0.35)	–
	1 if participants live in Midwest	0.23 (0.42)	–
	1 if participants live in west	0.19 (0.39)	–
	1 if participants live in south	0.36 (0.48)	–
Low Frequency	1 if eat fresh strawberries less than 2–3 times a month; 0 otherwise	0.45 (0.50)	–
Conventional & Warehouse	1 if purchase strawberries at conventional grocery stores or warehouse retailer; 0 otherwise	0.73 (0.44)	–
Natural food store	1 if purchase strawberries at natural foods grocery stores; 0 otherwise	0.08 (0.28)	–
Cooperatives & direct sales	1 if purchase strawberries at Food Cooperative or direct sale; 0 otherwise	0.05 (0.22)	–
Farmer's market	1 if purchase strawberries at famer's market; 0 otherwise	0.13 (0.34)	–
Brand	1 if think company's private brand is important information on strawberry labels; 0 otherwise	0.14 (0.35)	–
Local	1 if local or regional information is considered important on labels; 0 otherwise	0.30 (0.46)	–
Organic	1 if organic logo information is considered important on labels; 0 otherwise	0.40 (0.49)	–

(Continued)

TABLE 2. Continued

Variables	Description of Variables	Mean (SD)	U.S. Census
Health	1 if health-related information is considered important on labels; 0 otherwise	0.45 (0.50)	–
Sustain	1 if sustainably-grown information is considered important on labels; 0 otherwise	0.30 (0.46)	–
Safety	1 if safety-related information is considered important on labels; 0 otherwise	0.77 (0.42)	–
Non-GMO	1 if "not genetically modified" information is considered important on labels; 0 otherwise	0.22 (0.41)	–
Eco Label	1 if eco-label information is considered important on labels; 0 otherwise	0.34 (0.47)	–

TABLE 3. Model selection for Latent Class Logit Model

Classes	LLF	Number of Parameters	AIC	CAIC	BIC	Posterior Prediction Accuracy
2	−6688.02	17	13410.04	13511.49	13494.49	0.98
3	−6528.73	26	13109.45	13264.62	13238.62	0.93
4	−6428.18	35	12926.37	13135.25	13100.25	0.90
5	−6384.93	44	12857.86	13120.45	13076.45	0.90
6	−6245.88	53	12597.76	12914.06	12861.06	0.89

TABLE 4. Estimation Results of Latent Class Logit Model

Variables	Group 1: Balanced Consumers (66%)	Group 2: Experience Attribute Sensitive Consumers (18%)	Group 3: Search Attribute Sensitive Consumers (16%)
Price	−0.886***	5.260*	−1.485*
	(−3.53)	(1.90)	(−1.89)
External color	0.202***	−0.175	0.661***
	(10.86)	(−0.71)	(9.29)
Size	0.037**	0.355	0.137**
	(2.01)	(1.51)	(2.22)
Internal color	0.140***	1.305***	0.769***
	(6.96)	(10.70)	(10.55)
Firmness	0.137***	−0.265	0.442***
	(3.91)	(−0.91)	(3.81)
Flavor	0.195***	0.313**	0.161**
	(10.51)	(3.09)	(2.51)
Shelf-life	0.102***	0.495**	0.316***
	(5.49)	(2.18)	(5.36)

Note. t statistics in parentheses
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

two segments, the negative coefficient for price is significantly different from zero (at the 0.1% level), suggesting this group is very sensitive to price. In other words, this group values all of the preferred strawberry attributes but doesn't require the best quality level for each attribute. They are "balanced," caring about all the strawberry traits as well as price.

Group 2, 18% of the sample, consists of *Experience Attribute Sensitive Consumers*. The price coefficient for this group is positive and significant at 10% significance level. This indicates that for this group, purchasing strawberries may result in an increase in utility. This increased utility outweighs the decreased utility from spending money on strawberries (Ouma et al., 2007). With positive and significant coefficients for attributes such as internal color and flavor, Group 2 participants prefer strawberries with ideal red internal color and intense strawberry flavor, and these two attributes have the highest coefficients among three groups. The coefficient of shelf life is also significant at the 5% level, indicating this group of participants also cares about the shelf life of strawberry. In fact, the magnitude of the coefficient for shelf life for this group of participants is larger than that for the other two groups. Generally, these attributes (internal color, flavor, and shelf life) cannot be inspected and confirmed until purchase or use of the product, so consumers can only determine these attributes by "experience." Thus, this group is termed *Experience Attribute Sensitive Consumers* (Nelson 1974; 1970).

Group 3, *Search Attribute Sensitive Consumers*, accounts for 16% of the sample, Strawberry attributes such as external color, size, and firmness, which can be evaluated prior to use or purchase, are search attributes (Caswell & Mojduszka 1996; Nelson 1970, 1974). Based on our results from the latent class logit model, *Search Attribute Sensitive Consumers* exhibit strong preferences for ideal red external color, firm texture, and longer shelf life. Coefficients for external color and firmness are the highest across three segments and significant at the 0.1% level. This group also prefers larger fruit size, significant at the 5% level. The coefficient for price is negative and significant at 10% significance level, indicating this group is sensitive to the price of strawberries.

3.3 Sociodemographic Backgrounds and Purchasing and Eating Habits for the Three Segments

Based on the latent class logit model, we used the results from the membership function to compare the sociodemographic backgrounds and purchasing/eating habits across the three groups of participants (Pacifico & Yoo, 2012). Table 5 shows the results from the membership function. The mean coefficient for each demographic variable for the first two groups is tested for significance compared to the corresponding coefficient for the third group controlling for other variables. That is, the *Search Attribute Sensitive Consumers* serve as the reference group and their coefficients are normalized to be zero. In addition, since the results in Table 5 do not test if the sociodemographic backgrounds and purchasing habits are significantly different across the three groups, we further conducted ANOVA tests. The ANOVA tests compare the sample means between segments and the null hypothesis is that the means for demographic, purchasing habits, eating habits and attitudes are the same across groups. The summary of demographic variables and the ANOVA test p-values are presented in Table 6.

The ages of the participants are represented by three age levels: *Younger* age—18 to 34 years old; *Middle* age—35 to 54 years; and *Older* age—55 years and older. Compared to *Search Attribute Sensitive Consumers*, *Balanced Consumers*, and *Experience Attribute Sensitive Consumers* are less likely to be older, as the coefficients for the variable *Older* is negative and significant for both groups. The ANOVA results also indicate significant differences in terms of the percentage of *Older* consumers across the three groups: *Search Attribute Sensitive Consumers* have the highest percentage of *Older* consumers, followed by *Balanced Consumers* and *Experience Attribute Sensitive Consumers*.

Household size differs among groups. The membership function results show that compared to *Search Attribute Sensitive Consumers*, *Balanced Consumers*, and *Experience Attribute Sensitive Consumers* tend to have smaller household size.

TABLE 5. Estimation Results of Latent Class Logit Model Membership Function

Variables	Group 1:Balanced Consumers	Group 2:Experience Attribute Sensitive Consumers
Younger	−0.04	−0.08
Older	−0.44	−0.94***
Male	0.18	−0.26
Midwest	0.08	0.45
West	0.03	0.51
South	0.11	0.51
Education	−0.16	−0.13
Household size	−0.19*	−0.26*
Children	0.37	−0.04
Caucasian	0.42*	0.58*
Low household income (<25,000/year)	−0.61***	−0.62*
Low frequency	−0.64***	−0.84***
Conventional & Warehouse	0.55	0.67
Natural food store	0.69	0.58
Cooperatives & direct sales	−0.14	−0.24
Brand	0.49	0.01
Local	0.02	0.17
Organic	0.40	0.80**
Health	−0.31	0.23
Sustain	−0.13	−0.81**
Safe	0.42*	−0.14
Non-GMO	−0.10	−0.50
Eco-Label	0.13	0.44

Note. The reference group is group 3, the *Search Attribute Sensitive Consumers*.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.
Three age cohorts were used in this regression: Younger age—18 to 34 years old; Middle age—35 to 54 years; and Older age—55 years and older. The reference group is middle age group.

More of the *Balanced Consumers* and *Experience Attribute Sensitive Consumers* are Caucasian compared to *Search Attribute Sensitive Consumers*, and the difference is significant at the 10% level.

Consumers with annual household income less than $25,000 are considered low-income. The definition of low-income is based on poverty guidelines. For example, in 2014, the poverty level was set at $23,850 (total annual household income) for a family of four (U.S. Department of Health and Human Services, 2014). The proportions of low-income participants are lower for *Balanced Consumers* (significant at the 1% level) and *Experience Attribute Sensitive Consumers* (significant at the 10% level) compared to *Search Attribute Sensitive Consumers*. The ANOVA results indicate the three segments differ significantly in terms of percentages of low-income consumers.

Balanced Consumers are more likely to have children in the household, followed by *Search Attribute Sensitive Consumers* and then *Experience Attribute Sensitive Consumers*. The differences across groups are significant at the 5% level as indicated by the ANOVA test result.

As for the eating habits, eating frequencies vary significantly across groups. In comparison with *Search Attribute Sensitive Consumers*, *Balanced Consumers*, and *Experience Attribute Sensitive Consumers* eat strawberries more frequently (negative coefficients for low frequency), and the differences in frequency are significant at 1% level. The ANOVA results are also significant with a p-value less than 0.1%, which means *Experience Attribute Sensitive Consumers* eat strawberries most often, followed by *Balanced Consumers* and then by *Search Attribute Sensitive Consumers*.

We did not find significant differences among segments for the shopping outlets from membership function, but the ANOVA test results show a significant difference at the 5% level in the shopping preference across the three groups, specifically for farmers' markets.

TABLE 6. Demographic Backgrounds for Three Groups and ANOVA Test Statistics

Variable	Group 1: Balanced Consumers		Group 2: Experience Attribute Sensitive Consumers		Group 3: Search Attribute Sensitive Consumers	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Younger	0.44	0.02	0.46	0.04	0.40	0.03
Older***	0.22	0.02	0.18	0.03	0.31	0.03
Low Income**	0.18	0.01	0.20	0.03	0.26	0.03
Education	3.03	0.04	3.05	0.08	3.06	0.08
Male*	0.35	0.02	0.26	0.03	0.31	0.03
Caucasian	0.76	0.02	0.80	0.03	0.73	0.03
Household size	2.76	0.05	2.57	0.08	2.69	0.09
Children***	0.49	0.02	0.38	0.04	0.42	0.03
Low frequency***	0.42	0.02	0.39	0.04	0.59	0.03
Conventional & Warehouse	0.74	0.02	0.75	0.03	0.68	0.03
Natural food store	0.09	0.01	0.08	0.02	0.07	0.02
Cooperatives & direct sales	0.04	0.01	0.05	0.02	0.06	0.02
Farmer's market*	0.12	0.01	0.11	0.02	0.18	0.03
Brand**	0.16	0.01	0.12	0.02	0.09	0.02
Local	0.31	0.02	0.33	0.04	0.27	0.03
Organic***	0.41	0.02	0.46	0.04	0.31	0.03
Health	0.44	0.02	0.50	0.04	0.42	0.03
Sustain	0.32	0.02	0.25	0.03	0.28	0.03
Safety*	0.79	0.02	0.72	0.03	0.73	0.03
Non-GMO	0.23	0.02	0.18	0.03	0.21	0.03
Eco Label*	0.35	0.02	0.36	0.04	0.26	0.03
Share	65.60%		18.00%		16.40%	

Note. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$ denote the ANOVA p-values.
Three age cohorts were used in this regression: Younger age—18 to 34 years old; middle age—35 to 54 years; and older age—55 years and older. The reference group is middle age group.

Consumers' opinions about the usefulness of strawberry labels also differed significantly across the three groups. *Balanced Consumers* have a strong preference for private brands. Sixteen percent consider private brands as important, while only 12% of *Experience Attribute Sensitive Consumers* regard private brands as important, followed by a 9% of *Search Attribute Sensitive Consumers*.

Forty-six percent of *Experience Attribute Sensitive Consumers* and 41% of *Balanced Consumers* think organic labels are important, while only 31% of *Search Attribute Sensitive Consumers* prefer strawberries with organic labels. *Balanced Consumers* have a preference for food safety labels with 79% of them regarding food safety information as important, while 73% of both *Experience Attributes Sensitive* and *Search Attribute Sensitive Consumers* consider food safety labels as important. In addition, 38% of *Experience Attribute Sensitive Consumers* prefer eco-labels; in contrast, only 26% of *Search Attribute Sensitive Consumers* think the environmentally friendly information is important. These differences are significant in both the membership function and the ANOVA results.

4. CONCLUSIONS AND DISCUSSION

The consumer preference results presented in this study are useful information for strawberry breeders, growers, and market intermediaries (e.g., packers, shippers, marketers) when they consider to develop and invest in improved strawberry cultivars to satisfy diverse consumer preferences. In addition, the findings on consumer segmentation provide guidance for the fresh market strawberry industry in setting selling strategies to target different consumer segments.

Three segments of consumers (*Balanced Consumers*, *Experience Attribute Sensitive Consumers*, and *Search Attribute Sensitive Consumers*) were identified based on differences in their demographic backgrounds and fruit consuming habits. In general, *Balanced Consumers* valued all six strawberry traits considered in this study. These consumers prefer strawberries with ideal red external and internal colors, firmer texture, intense flavor, longer shelf life, and larger size. They differ from *Experience Attribute Sensitive Consumers* in that the retail price significantly affects this group's preferences and purchasing decisions. In other words, *Balanced Consumers* are sensitive to price change, and as the price goes higher they will be less likely to purchase strawberries. *Balanced Consumers* are likely in the 35–54 year old age cohort, with annual household income higher than \$25,000. They are more likely to have children, care about a food safety labels and private brands. *Balanced Consumers* are notably the largest group of consumers, accounting for around two-thirds of our study sample. The large proportion of *Balanced Consumers* suggests that there will be a potential market for strawberries with combined desired attributes of ideal read external and internal colors, firm texture, intense flavor, large size, and longer shelf life. Therefore, strawberry breeders and growers should focus on breeding and growing strawberry cultivars with such characteristics.

Experience Attribute Sensitive Consumers have a stronger preference—compared to the other two groups—for experience attributes such as intense strawberry flavor, ideal red internal color, and longer shelf life. Consumers in this group are in the younger age group (18–34 year old), with an annual household income higher than \$25,000, and the least likely to have children. They also eat strawberries with a higher frequency compared to the other two groups. Eighty percent of this group is Caucasian and 74% female. It is worth noting that even though *Experience Attribute Sensitive Consumers* account for less than one third of the whole sample, they purchase strawberries most frequently, make purchasing decisions based on their experiences, and are the least sensitive to price changes. Therefore, fulfilling the needs for this group could be profitable for the strawberry industry. Strawberry breeders should focus on strawberry cultivars with improved flavor; ideal internal red color, and longer shelf. In addition, this group is more likely to purchase fruit produced organically.

Search Attribute Sensitive Consumers care about the external color, firmness, and size; they also care about internal color and flavor when making purchasing decisions, but the preferences for these two traits are not the strongest among the three groups. On average, consumers in this group are older (55 years or older), have the lowest income (less than \$25,000 annual household income), and the lowest proportion of Caucasians. Strawberry cultivars with improved search attributes such as better appearance, firmer texture, and larger size are needed to target this segment. However, as this group is sensitive to price, growers and market intermediaries need to find ways to produce these varieties efficiently (e.g., minimizing cost but maintaining product quality) so they can offer these strawberries at competitive prices. Marketing strategies such as using in-store coupons could be useful to retailers to attract more *Search Attribute Sensitive Consumers*. Demand from this consumer segment would be fostered if producers meet consumers' threshold levels for key quality attributes (appearance, firmness, and size) and at the same time being efficient in the use of production inputs to lower cost.

Our study has some limitations. For example, we did not test or control for the potential ordering effect of attributes in the choice experiment. Future studies could consider randomizing the attribute order across different scenarios to test and control the attribute order effect.

In conclusion, the identification and characterization of U.S. strawberry consumer segments in this study will help breeders and growers to prioritize key traits and the desired levels of those traits. Further, it provides insights to the fresh market strawberry industry to develop strategies to target different consumer segments.

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