Are Consumers Willing to Accept Gene Edited Fruit? An Application to Quality Traits for Fresh Table Grapes

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Abstract

This paper compares consumers' willingness to pay (WTP) for selected quality attributes of table grapes developed using two different breeding technologies. Data were collected using an online survey that included a discrete choice experiment in a between-subjects experimental design. In the choice experiment, one group of respondents considered table grapes developed using gene editing (CRISPR-Cas9) and the other considered table grapes developed using conventional breeding. The highest WTP value across attributes was for sweetness, followed by crispness, flavor, skin color, and size. The rank order of the WTP values for the table grape attributes was the same for both breeding technologies; however, the magnitude of the WTP for the specific attributes differed between grapes produced using conventional breeding and gene editing: in some cases, a statistically significant discount and in others a statistically significant premium for attributes of grapes produced using gene editing. The point estimates indicated a slight discount in overall WTP for table grapes produced using gene editing compared with conventional breeding, but this discount was neither economically nor statistically significant. Results from a latent class model revealed the presence of consumer segments who are heterogeneous in their WTP for table grapes developed by gene editing.

Keywords: Consumer preferences, gene editing, plant breeding, table grapes, willingness to pay.

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1. Introduction

Consumers are becoming increasingly attentive to the food technologies used to develop, produce, process, and preserve foods (Cox and Evans, 2008). While some new food technologies (such as freezing, pasteurization, chemical and biological preservatives) are generally accepted today by consumers after some early trepidation, some others (such as food irradiation and genetic engineering) continue to experience significant and longstanding market resistance (Wunderlich and Gatto, 2018; Yang and Hobbs, 2020). Despite the scientific community having established that specific new technologies are safe and effective, many consumers exhibit aversion and distrust, and are said to perceive the technologies themselves or the foods they are used to produce as risky, unethical, or unnatural (Frewer, 2003; Siegrist, Hartman, and Keller, 2013). Funk and Rainie (2015) reported that while 88% of the scientists affiliated with the American Association for the Advancement of Science (AAAS) regard genetically engineered foods as safe to eat, only 37% of the U.S. public consider these technologies as safe (Yang and Hobbs, 2020). Lusk, Roosen, and Bieberstein (2014) assessed whether consumers are more prone to tolerate risks associated with new technologies if they perceive that the technologies bring direct benefits to themselves rather than to other groups in society, such as agricultural producers, food manufacturers or other individuals. However, the notion of benefit depends largely on individuals' perceptions of what constitutes a benefit and individual differences in perceptions; therefore, it is argued that consumers will less easily accept novel products or technologies that do not bring a tangible direct benefit to them (Frewer, 2003; Lusk, McFadden, and Rickard, 2015).

Given the on-going interest in new plant breeding technologies beyond genetic engineering, this study centers on the breeding technology called gene editing or CRISPR-Cas9 (hereafter gene editing). Genome editing technologies enable scientists to make changes to DNA, leading to changes in physical traits, like eye color, and disease risk. Scientists use different technologies to do this. CRISPR-Cas9 is a recent powerful specific innovation in that generic class of genome editing technologies (U.S. National Institutes of Health, 2019). These technologies act like scissors, cutting the DNA at a specific spot. Then scientists can remove, add, or replace the DNA where it was cut. According to the National Human Genome Research Institute CRISPR is simpler, faster, cheaper, and more accurate than older gene-editing methods and hence many scientists who perform gene editing now use CRISPR (U.S. National Institutes of Health, 2019). As described by Menz et al. (2020), by 2020 the use of gene editing by plant breeding programs was rapidly expanding, as more and more plants with market-oriented traits were being developed, and companies had already released genome-edited crops to the market. For instance, gene-editing methods were applied to rice, tomato, maize, wheat, potato, soybean, citrus, and livestock (Hefferon and Herring, 2017). For the crops listed, gene editing has been used to influence agronomic traits, food and feed quality, and biotic stress tolerance. Across countries, most publications of the application of gene editing in crops were authored by scientists that work at universities and institutions in China, followed by the United States, and Japan.

Most of the current regulations on genetic innovations in agriculture are centered on the use and commercialization of genetically engineered (GE) crops (Menz et al., 2020). In March 2018, the U.S. Department of Agriculture issued a statement to clarify the regulations for "plants produced through innovative new breeding technologies which includes technologies called gene editing." (U.S. Department of Agriculture, 2018). Specifically, the statement indicated that the U.S. Department of Agriculture did not regulate "plants that could otherwise have been developed through traditional breeding technologies as long as they are not plant pests or developed using plant pests." The statement encompasses new technologies that are increasingly being used by plant breeding programs, including gene editing, because "they can introduce new plant traits more quickly and precisely, potentially saving years or even decades in bringing needed varieties to farmers." Among other things, it implies that plants, animals, and food ingredients that were developed using gene editing need not be labeled as such, unlike those developed using genetic engineering, which must be labeled as such according to PL 114–216 (see, e.g., Bovay and Alston 2018).

The objectives of this study are twofold. First, we assess the differences in the WTP for selected fruit quality traits of table grapes, described as being developed using either conventional breeding or gene editing. A mixed logit estimation was applied to data collected via a discrete choice experiment in a U.S. nationwide consumer survey. Second, we identify consumer segments that differ in their WTP for table grapes produced using either breeding technique. We applied a latent class model to identify segments within our consumer sample and estimated differences in WTP for table grapes across segments, for a given breeding technique. The latent class model identifies potential sources of preference heterogeneity, and the impact of sociodemographics, sources of trusted information and level of knowledge of gene editing.

This study is motivated by the idea that consumers tend to perceive a new plant breeding technology as less risky if the benefits from using such technology are direct and tangible to consumers. Therefore, we contribute towards a better understanding of how preferences for consumer-related attributes (in this instance, quality attributes of fresh produce) vary according to the plant breeding technology used. Also, our findings will help to inform the phenotyping and genetics research community about consumer demand for specific traits in new table grape cultivars (VitisGen2, 2018). As mentioned, this study is centered on table grapes; 99% of the table grapes commercially grown in the United States are produced in California (California Table Grape Commission, 2021). In 2020, California's 122,000 bearing acres of table grapes produced 1.19 million tons of table grapes valued at 1.47 billion dollars at the farm gate (U.S. Department of Agriculture, 2021).

2. Review of literature

Because this study examines the acceptance of gene-editing technology, as it affects consumers' willingness to pay for table grape quality attributes, we briefly review studies of consumers' acceptance of gene-editing breeding technologies and studies of consumers' preferences for table grape quality traits.

2.1 Consumers' acceptance for gene-edited crops

Shew et al. (2018) conducted an "artifactual field experiment" using an online survey in five countries (United States, Canada, Belgium, France, and Australia) to assess consumers' willingness to consume and WTP for gene-edited rice compared with conventional and GE foods. They found that respondents were more willing to consume gene-edited rice than GE rice; however, WTP was lower for both gene-edited and GE rice than for the conventionally bred product, with a larger discount in Belgium and France compared with the United States, Canada, and Australia. The authors conclude that consumers who already choose not to eat GE foods might show similar preferences for gene-edited foods.

Yan and Hobbs (2020) conducted a nationwide survey in Canada to investigate the framing effects of information on the WTP for apples; here they tested for the impacts of information that described how edible coating, genetic engineering, gene editing (CRISPR) and conventional breeding methods affect the degree of browning, the enhancement with antioxidants, and production characteristics. They found that the non-browning attribute has a larger effect on consumer demand than does information that the apples contain an enhanced level of antioxidants. Respondents stated a price discount for gene editing, genetic engineering, and edible coating; overall the smallest discount was for gene editing. Researchers also found that layperson narratives mitigated the negative responses to gene editing and genetic engineering more than the logical-scientific information did.

Muringai, Fan, and Goddard (2020) conducted an online survey in Canada to investigate how respondents' acceptance of GE potatoes would be affected by the trait to be introduced, the type of breeding technology, and the nature of the developer of the technology (government versus the private sector). Their results suggest that the respondents perceived greater benefits from health-related attributes (lower acrylamide released when potatoes are fried) than from environmentally related attributes (pesticide and food waste reduction). Respondents were willing to pay discounted prices for gene-edited or GE potatoes compared to conventional breeding. However, they found that consumers were more accepting of products from gene editing than genetic engineering. Respondents preferred potatoes developed by the government rather than the private sector (i.e., Monsanto, J. R. Simplot, etc.)

Marette, Disdier, and Beghin (2021) conducted economic experiments in France and the United States to compare consumers' attitudes and WTP for gene-edited apples that do not brown. They found that in both countries, participants stated a price discount for GE and gene-edited apples, with a larger discount for GE than for gene-edited apples. Also, the discount is smaller in the United States than in France. In the United States, the disclosure of benefits related to the gene-edited apples led to a price premium compared to the conventionally bred apples, however such premiums were not observed among French participants.

In sum, several recent studies show that consumers are generally more accepting of gene edited products than GE products. However, the extent of this greater acceptance might depend on the nature of the innovation and thus the benefit perceived by the consumer. The present study extends research in this arena by examining if the breeding method used (conventional breeding versus gene editing) affects consumers' willingness to pay for selected fruit quality attributes for table grapes.

2.2. Consumers' preferences for table grape quality traits

Studies centering on identifying the organoleptic attributes of table grapes most appealing to consumers concur that overall preference is positively correlated with taste, sweetness, acidity, crunchiness, and external appearance. This section covers studies in the sensory science discipline. Crisosto and Crisosto (2002) studied consumer acceptance of 'Red Globe' grapes in a panel of 400 American and 250 Chinese consumers. They found that consumer acceptance was positively correlated with high acidity, expressed as titratable acidity (TA), and sweetness, expressed as soluble solids concentration (SSC). Jayasena and Cameron (2008) conducted an evaluation of consumer acceptance of 'Crimson Seedless' table grapes with 63 Australian panelists. They found that overall liking of grapes was positively correlated with SSC content, acidity, and the ratio of SSC to acidity.

Ma et al. (2016) describe color as a direct sensory characteristic of table grapes as it influences consumers' perceptions of grape attractiveness and taste. The authors state that grapes with intense perfume, and those that are plump, juicy, and sweet are more desired by consumers. They conducted a sensory taste evaluation panel with 10 individuals in China to analyze consumers' preferences for attributes of the table grape variety 'Kyoho.' They found that, among the attributes examined, taste had the highest correlation with overall acceptability, followed by odor, texture, and surface cleanliness or berry bloom.

Chironi et al. (2017) assessed consumers' preferences across 22 sensory attributes for the fresh table grape varieties 'Italia' and 'Red Globe' in a sample of 1,000 consumers in Sicily. They found that the consumers preferred the variety 'Italia' (white berries) for its visual appearance and taste, and 'Red Globe' (red berries) for its crunchiness and intense berry aroma. They concluded that preferences for quality attributes vary according to the variety of grape.

3. Data

Our study used choice experiments to collect information about how consumers value specific traits in table grapes. The data were collected online via the survey platform Qualtrics, during April 1–13, 2020. After incomplete responses were removed, the survey included responses from a total of 2,873 participants, comprising subjects that: (1) collectively were consistent with a random representation of U.S. demographics in terms of age and geographical location, and individually (2) were in charge of the grocery shopping in the household, and (3) had consumed table grapes during the previous three months. To ensure the latter was accomplished, respondents were asked a screening question to indicate their consumption of table grapes within a given timeframe.

To examine the effect of the breeding technology on the WTP for table grape quality attributes, a between-subjects design was used. Two versions of the survey were developed, and they were distributed randomly among respondents, resulting in almost equal-sized samples for the two versions. The only difference between the two survey versions was that before being presented the discrete choice experiment questions, respondents were informed that the products they would evaluate were from one of the two breeding technologies for table grapes (either conventional breeding or gene editing). Both versions of the survey presented a brief description of the two breeding technologies (see Appendix A).

To ascertain choice behavior, each respondent was given eight scenarios to mimic a grocery shopping experience for table grapes. Before the scenarios were presented, it was stated whether the table grape variety was developed by conventional breeding or gene editing. Each scenario consisted of two purchase options, A and B, which differed in terms of the physical attributes of the grapes (including fruit size, skin color, crispness, sweetness, flavor) and the price ($1.98/lb and $2.98/lb). In each scenario, consumers were asked to select only one option among three: they could choose option A, option B, or neither A nor B (which was labelled as option C in each scenario). An example of a choice scenario is presented in Figure 1. The selected list of table grape quality attributes was based on previous sensory-related studies (Ma et al., 2016; Chironi et al., 2017; Crisosto and Crisosto, 2002; and Jayasena and Cameron, 2008); and on consultations with table grape breeders and industry representatives.

Table 1 presents the list of attributes and the set of possibilities for each attribute. The JMP® software was used to generate a fractional factorial design with random combinations of attributes in each scenario. The JMP® software employs a two-step procedure using an algorithm taken from Kessels, Jones, and Goos (2011). The fractional factorial design minimized the number of scenarios, mitigating potential respondent fatigue while maximizing the D-efficiency. Both survey versions are based on a 2^6 design, that would have initially yielded 64 scenarios, with the fractional factorial the design ended with 8 scenarios. The design maximized the D-efficiency value at 99%.

There were 1,422 respondents in version 1 (conventional breeding) and 1,451 respondents in version 2 (gene editing) of the survey. In addition to the discrete choice questions, respondents were asked about their preferences for table grape attributes, their table grape consumption, and their perceptions about science and technology. Finally, they were asked a series of questions about their sociodemographic details.

4. Empirical approach

The empirical approach of this paper is based on Lancaster (1966) and McFadden (1974). First, following Lancaster (1966) we assume that consumers derive utility from the attributes inherent to the good rather than the good itself. From McFadden (1974) we follow random utility theory and model the utility of the consumer as being composed of a deterministic component, given by the good's attributes, and a random component, given by unobserved factors.

We use a mixed logit model to estimate the parameters. The advantage of a mixed logit model over a standard logit or a conditional logit model is that it relaxes the assumption of independence of irrelevant alternatives (IIA), allowing preference parameters to vary randomly across consumers following a probability distribution (Train, 2009). The mixed logit model follows,

$$U_{ni} = \alpha_j + \beta_n x_{ni} + \gamma p_i + \varepsilon_{ni} \quad (1)$$

where U_{ni} is the indirect utility derived by individual *n* when choosing alternative *i* out of a total of *j* alternatives in the choice set *J*, α_j is the Alternative Specific Constant (ASC) denoting the opt-out option, x_{ni} denotes the observed attributes of choice, see details in Table 1, β_n is an unobserved vector of random coefficients for each individual, n that is assumed to follow a multivariate normal distribution with density $f(\beta_n|\theta)$, where θ is the true parameter vector of the distribution, p_i is the represents price, γ is the estimate for price and is assumed to be fixed, and ε_{ni} is an unobserved error term that is assumed to be identically and independently distributed (Train, 2009).

Conditional on β_n, the probability that individual n chooses alternative i, is

$$Pr_{ni} = L_{ni}(\beta_n) = \frac{exp(\beta_n x_{ni})}{\sum_{j=1}^{J} exp(\beta_n x_{nj})}. \quad (2)$$

As β_n is unknown, we employ the unconditional probability, which is the integral of the conditional probability over all possible values of β, which depends on the distribution of β,

$$Pr_{ni}(\theta) = \int Pr_{ni} \, f(\beta_n|\phi) d\beta_n \ . \quad (3)$$

Then, the probability of individual n making a sequence of choices is

$$Pr_n = \prod_{j=1}^{J} \left(\frac{exp(\beta_n x_{ni})}{\sum_{j=1}^{J} exp(\beta_n x_{nj})} \right)^{y_{ni}}, \quad (4)$$

where y_{ni} denotes an indicator function that is one (1) if consumer n chooses alternative i, and zero (0) otherwise. Maximum likelihood estimation solves for $\hat{\beta}$ that maximizes the log-likelihood function, which is specified as:

$$lnL = \sum_{n=1}^{N} \sum_{i=1}^{J} y_{ni} \ \ln(Pr_n), \quad (5)$$

where ln L denotes the sum of the likelihood functions across options (Train, 2009). The coefficients were estimated using STATA. The estimate of WTP by individual n for attribute x is obtained by dividing the individual-specific bootstrapped coefficient estimate for that attribute by the individual-specific bootstrapped coefficient estimate for price, multiplied by -1:

$$WTP_{n_{atttibute_x}} = \frac{-\beta_{n_{atttibute_x}}}{\beta_{n_{price}}} \quad (6)$$

where $WTP_{n_{atttibute_x}}$ is the WTP for attribute x, $-\beta_{n_{atttibute_x}}$ is the estimated coefficient for attribute x, and $\beta_{n_{price}}$ is the estimated coefficient for price, all specific to respondent n.

A pairwise t-test is used to assess the respondent's WTP for each quality attribute of table grapes; here we evaluate if there were statistically significant differences between the consumers who were presented grapes produced using conventional breeding versus those who were presented grapes produced using gene editing. The difference in WTP for each quality attribute, between the two breeding technologies, is also measured by applying the nonparametric combinatorial resampling approach developed by Poe, Giraud, and Loomis (2005). Finally, the aggregated WTP for one pound of table grapes, produced using conventional breeding versus gene editing, was calculated. This used the bootstrapped individual coefficient estimates for each of the quality attributes and price ($3/lb was used as a reference price). The bootstrap yielded a vector, for each individual respondent, of estimated WTP for each attribute. Next, a t-test was used to test whether WTP differs, depending on the breeding technique used. A latent class analysis was done to see if the aggregated WTP for table grapes differed across classes of consumers for each breeding technique.

4.1 Latent class model

The latent class model captures the heterogeneous preferences and identifies segments within the sample of survey respondents, namely classes. Preferences across classes are heterogeneous, but preferences within each class are assumed to be homogeneous (Ouma, Abdulai, and Drucker, 2007). Mathematically, the probability that individual *n* will choose alternative *i* in choice scenario *j* for latent class *c* is:

$$Pr(nij|c) = \frac{\prod_{j=1}^{J} e^{\beta_c x_{nij}}}{\sum_{i=1}^{I} e^{\beta_c x_{nij}}}, \qquad (7)$$

where x_{nij} is the vector of observed attributes associated with alternative i and β_c is the coefficient estimate for the class-specific utility. A fractional multinomial logit model is used to estimate the probability that individual *n* belongs to class *c*:

$$Pr(c) = \frac{e^{\theta_c m_n}}{1+\sum_{c=1}^{C-1} e^{\theta_c m_n}} , \tag{8}$$

where m_n is the set of observable individual characteristics that affects the class membership, θ_c is a vector of estimable coefficients associated with the class (Ouma, Abdulai, and Drucker, 2007, Greene and Hensher, 2003). After the probabilities of an individual being in each class have been estimated, each individual is assigned to the class with the highest probability. The aggregated WTP for table grapes (for each of the two survey versions) was estimated for each of the classes identified.

To identify the number of classes, measures of goodness of fit such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are commonly used; the best-fitting model is the one with the smaller AIC and BIC. Table 2 presents the goodness-of-fit statistics for two, three, and four classes. Based on the AIC and BIC criteria alone, the number of classes should be four. However, across both survey versions a larger number of membership class variables are statistically significant in the model with three classes than in the model with four classes, which indicates that the model with three classes outperforms the model with four (Nylund-Gibson & Choi, 2018). For this reason, a model with three classes is preferred. Further, past research supports using the statistical significance of the parameter estimates in each class, the interpretability of the parameter estimates, and the number of observations in each class as additional criteria to select the optimal number of classes (Green & Hensher, 2003; Pacifico & Yoo, 2012).

5 Results

This section presents the results from the statistical analysis of the survey responses. Before discussing the results of the choice experiments, we present evidence on the sociodemographic characteristics of the respondents to the two versions of the survey, hoping to find that the two groups of respondents were similar to one another and also representative of the broader U.S. population.

5.1 Sociodemographic characteristics of respondents

Tables 3 and 4 present the sociodemographic characteristics of the respondents for the two versions of the survey and compares them with the corresponding information from the U.S. Census data (U.S. Census, 2018). Overall, across both survey versions, 59% of the respondents in the sample are female (59% and 58% for version 1 and version 2 respectively); the average age of the respondents is 42 years, and the average household size is three individuals; 75% of the respondents are of white ethnicity (version 1: 76%, version 2: 74%); 30% obtained a four-year college degree (version 1: 31%, version 2: 28 %); average annual household income is about \$98,500 (version 1: \$98,577, version 2: \$98,571); 18% of the respondents live in a rural area (version 1: 19%, version 2: 17%) while the rest live in either urban or suburban area; 17% are vegetarian (version 1: 20%, version 2: 14%); and 26% (version 1: 28%, version 2: 24%) respondents have worked or lived on a farm or ranch.

Compared with the 2018 U.S. Census averages, the sample of respondents is composed of more females, a larger proportion of white individuals, a larger proportion of individuals with at least a four-year college degree, and on average, individuals with higher income (U.S. Census, 2018). However, our survey respondents follow the profile of individuals who tend to be more responsive to surveys (Curtin, Presser, & Singer, 2000). Table 4 shows the results from pairwise t-tests for differences in the age, household size, number of people under 18 in the household and household income across the two survey versions. Results suggest that the means of the above-mentioned demographic variables are not different between the two survey versions.

Given that we used a between-subjects design, we further examine whether respondents to survey version 1 differ from respondents to survey version 2; this comparison was done across variables describing respondents' shopping and eating habits, ratings of importance of table grape quality attributes, label information, trusted sources of information, and perceptions of breeding methods. Results are presented in Appendix B, Tables B1–B5.

Table B1 presents the frequency distribution of the respondents' shopping and eating habits. On average, 36% (version 1: 35%, version 2: 36%) of the respondents in the sample consume table grapes every 2–3 weeks. The average quantity of table grapes bought per grocery shopping trip is 2.65 pounds per grocery shopping trip (version 1:2.7, version 2: 2.6). On average, 59% of the respondents (version 1: 58%, version 2: 60%) preferred pre-bagged table grapes while 48% indicated that their favorite type of table grape is green (version 1: 49%, version 2: 47%).

Table B2 presents the rankings of importance for a list of table grape traits. The trait with the highest mean ranking is "freshness" (4.5 out of 5) followed by "juiciness" (4.3 out of 5) for both versions of the survey. Table B3 presents ratings of importance for different pieces of information displayed on the labels. The most important label information for consumers was "seedless" (version 1: 4.1, version 2: 4.0) followed by "pesticide free" (3.8 for both the versions).

Table B4 presents the ratings of importance for alternative trusted sources of information when making food purchase decisions. The most-trusted sources of information for consumers are “friends and family” (version 1: 4.1, version 2: 4.0) and “medical professional” (version 1: 4.1, version 2: 4.0) while the least-trusted source of information is “social media” (2.8 for both versions). Table B5 presents results from questions we asked subjects concerning their awareness and level of knowledge about crop breeding and agricultural production methods. Respondents say they are less informed about gene editing compared with conventional breeding and genetic engineering; respondents also consider organic farming to be the safest, most natural, and ethical production method across both survey versions. The mean ranking of willingness to purchase fresh grapes produced using conventional breeding is 4.1 (for both survey versions) while for grapes produced using gene editing it is 3.5 and 3.4 for version 1 and version 2 respectively.

A pairwise t-test was conducted to test whether the rankings presented in Tables B1–B5, differ across the two survey versions. Results suggest no consistent statistically significant difference in the ranking of the variables, with a few exceptions. For example, respondents taking version 1 differ from respondents taking version 2 in their trusted sources of information: respondents to version 1 had a higher rating on the level of trust for individual farmers, friends and family members, and medical professionals than respondents to version 2 (Table B4). A similar result was obtained on the importance assigned to perceptions about breeding and production methods, yet the difference here is smaller: compared with respondents to version 2, respondents to version 1 indicated that they are more informed about organic farming, they consider conventional breeding and organic farming as natural, and consider organic farming as more ethical or morally acceptable. Overall, the results from the pairwise t-tests suggest that the samples respondents to the two versions of our survey are similar and are not significantly different from each other.

5.2 Mixed logit results

Table 5 presents the mixed logit results for both survey versions. Across both survey versions, the coefficient estimate for price is negative and statistically significant, indicating that the utility of respondents decreases as price increases. The coefficient estimates for sweet vs not sweet, crisp vs not crisp, and fruity flavor vs neutral flavor, are positive and statistically significant, indicating that respondents derive greater utility when table grapes are sweet, crisp, and flavorful. Similarly, the coefficient estimate for fruit size is positive and statistically significant indicating that consumers derive greater utility from grapes with berries larger than ¾ inch vs smaller than ¾ inch. These results are consistent with previous studies showing that consumers prefer table grapes that are flavorful, sweet, and crisp (Crisosto and Crisosto, 2002; Jayasena and Cameron, 2008; Ma et al., 2016; and Chironi et al., 2017). Lastly, respondents derive greater utility from grapes that are 100% green compared with grapes that are 50% green and 50% amber/yellow blush.

The ASC representing the no-purchase option (C) was negative but not statistically significant, indicating that respondents were indifferent between alternatives A or B and the no-purchase option, in each discrete choice scenario. The estimated standard deviations are statistically significant for all the quality attributes (we assumed that the coefficient for price and the ASC are deterministic constants while the coefficients of the other traits are normally distributed random variables) in both versions. This indicates significant heterogeneity of preferences among respondents for all the attributes. A likelihood-ratio test of joint significance of the standard deviations is rejected, which implies that not all standard deviations are equal to zero.

The bootstrapped WTP results are presented in Table 6. In general, regardless of the breeding method for table grapes, attribute by attribute, consumers are willing to pay the largest price premium for sweetness, followed by crispness, fruity flavor, 100% green color, and larger berry size (compared to the reference point of ¾ inch diameter). The results presented in the previous sections indicated that there were no major observable differences between the samples of respondents to version 1 (conventional breeding) and version 2 (gene editing) of the survey, and therefore we can usefully compare the WTP estimates between the two.

To compare the WTP for grape characteristics between the two versions, representing the two breeding methods, estimates of individual WTP for each respondent were bootstrapped and the bootstrapped means were compared using a t-test (Table 6). The t-test results suggest that WTP is statistically significantly different between the two versions at the 5% level of significance for each of the attributes except size, for which WTP is statistically significantly different at the 10% level of significance. Results from a nonparametric combinatorial resampling approach (Poe, Giraud, and Loomis, 2005) yield the same results as the pairwise t-test comparisons. WTP is higher for the attributes of flavor, crispness, and size, but lower for the attributes color and sweetness when grapes are produced using conventional breeding rather than gene editing. This is surprising and a little difficult to interpret. We offer ***no theory*** as to why consumers would pay ***a greater premium*** for certain attributes (color and sweetness) if they were developed using gene editing rather than conventional breeding. We do have some theory for why they would conversely (as anticipated) impose a discount for other attributes (flavor, crispness and berry size) if they were developed using gene editing. These findings might well be more indicative of the hypothetical nature of the study and might vanish with larger samples, or experiments conducted using actual grapes rather than pictures. The fact that we have some on each side contributes to why the overall WTP is not different between the two versions.

The aggregated WTP estimates across all selected quality attributes in this study are also presented in Table 6. The point estimates suggest that consumers are willing to pay a slightly higher price for table grapes developed using conventional breeding rather than gene editing ($2.12/lb vs. $2.09/lb) but this difference is neither statistically nor economically significant. This finding differs from reports by Yang and Hobbs (2020), Marette, Disdier, and Beghin (2021) who estimated a statistically significant price discount for fresh apples developed using gene editing rather than conventional breeding, and Muringai, Fan, and Goddard (2021) who found a statistically significant discount for potatoes developed using gene editing compared to conventional breeding.

Results from the latent class model for conventional breeding and gene editing are presented in Tables 7 and 8, respectively. In both survey versions, three distinct classes of consumers are identified. In survey version 1, which introduced grapes produced using conventional breeding, the classes identified are class 1 (27% of all respondents to survey version 1) as "little knowledge," class 2 (44% of all respondents) as "some knowledge," and class 3 (29% of all respondents) as "large knowledge" about gene editing as a breeding method. The mean WTP for grapes developed using conventional breeding is $1.76/lb for class 1, $2.07/lb for class 2, and $2.54/lb for class 3. The WTP differs between classes 1 and 3, and between classes 2 and 3, and this result is statistically significant, while no such difference exists between classes 1 and 2. Considering the available sociodemographic characteristics, class 3 has the largest percentage of males (66% of all respondents to survey version 1), millennials (66%), income above or equal to 100K (54%), and households with children younger than 18 years

(54%). Among sources of information, for classes 2 and 3, friends and family are significant (74% class 2, and 90% class 3), government agencies are notable (69% class and 84% class 3), science journals are influential (88% class 2, and 81% class 3), and scientific associations matter (96% class 2, 83% class 3); and for class 3 alone, media (81%) and social media (78%) are important. Members of class 3 consider themselves to be knowledgeable about gene editing (83%), and consider food produced using gene editing to be safe to eat (85%), natural (85%), and ethical (89%).

In survey version 2, which introduced grapes produced using gene editing, the classes identified are class 1 (30% of all respondents to survey version 2) as “little knowledge,” class 2 (43% of all respondents) as “some knowledge,” and class 3 (27% of all respondents) as “large knowledge” about the gene editing breeding method. The mean WTP for grapes developed using gene editing are \$1.72/lb for class 1, \$1.92/lb for class 2, and \$2.76/lb for class 3. Like survey version 1, WTP differs between classes 1 and 3, and classes 2 and 3 are different and this result is statistically significant, while no such difference exists between classes 1 and 2. Class 3 has the largest percentage of males (65% of all respondents to survey version 1), millennials (64%), income greater than or equal to 100K (61%), and households with children younger than 18 years (73%). Classes 2 and 3 rated friends and family (73% class 2 and 87% class 3), government agencies (66% class 2 and 86% class 3), medical professionals (87% class 2, and 91% class 3), science journals (88% class 2, 84% class 3), and scientific association (94% class 2 and 85% class 3) as important sources of information, whereas class 3 preferred media (87%) and social media (79%). Eighty-nine percent of class 3 respondents consider themselves to be knowledgeable about gene editing and consider food produced using gene editing to be safe to eat (88%), natural (86%), and ethical (88%).

Comparing the mean WTP for table grapes across classes for each breeding method, the results suggest that the overall WTP for table grapes developed using either conventional breeding or gene editing increases as the level of knowledge about gene editing increases. This result differs from findings by Vecchione et al. (2015) who conducted a survey of supermarket consumers in New Jersey and found a negative correlation between knowledge of genetic engineering and acceptance of GE products.

When comparing the WTP across class segments and surveys, it is notable that the WTP for table grapes developed using conventional breeding ranges from \$1.76/lb to \$2.54/lb while the WTP for table grapes developed using gene editing ranges from \$1.72/lb to \$2.76/lb. These results indicate a greater dispersion of WTP for grapes developed by gene editing compared with grapes developed by conventional breeding.

6. Summary and Conclusion

This study estimates consumers' WTP for quality attributes in table grapes introduced using either conventional breeding or gene editing. Utilizing a U.S. nationwide online survey of 2,873 consumers, we find that respondents prefer table grapes that are sweeter (compared to not sweet), crisp (compared to not crisp), with fruity flavor (compared to a neutral flavor), larger berries (larger than ¾ inch compared to smaller than ¾ inch), and more uniform color (100% green compared to 50% green and 50% amber/yellow blush).

The rank order of the WTP estimates under both breeding methods indicates that respondents are willing to pay the highest premium for sweetness, followed by crispness, fruity flavor, larger berries and uniform color. Our findings suggest that although the order of importance of attributes is the same for both breeding methods, the magnitudes of WTP for the individual attributes differ significantly between the two breeding methods.

We also found that while, on average, our sample of respondents were willing to pay slightly less for table grapes developed by gene editing ($2.09/lb vs. $2.12/lb) this difference is economically negligible and statistically insignificant. Results from the latent class segmentation analyses suggest a greater dispersion of WTP among consumers for grapes developed by gene editing compared with grapes developed by conventional breeding. In general, the WTP for either conventionally bred or gene-edited grapes increases as the level of knowledge about gene editing increases, and with increases in the perception that grapes developed using gene editing are safe, natural, and ethical to eat.

In the case of GE food, the technology has been subject to regulatory requirements, environmental activists have actively opposed the technology, and many consumers and others in the United States hold negative perceptions about the technology and the food produced using it. The status of GE food is even more limited in most other developed countries, giving rise to concerns over the market potential for other modern breeding methods such as gene editing. However, though the commercialization of gene editing is still in its infancy, consumers appear to be more accepting of food developed using gene editing. Given that the U.S. Department of Agriculture announced that it will not regulate plants that have been modified using gene editing, coupled with the results in this study showing that some consumer segments accept this technology, gene editing appears to be a promising avenue for plant breeding programs.

Our results suggest that agribusiness companies can potentially identify consumer segments that may be more accepting of this new technology and can potentially target them initially as a first step towards wider acceptance in the marketplace. Future work should extend our analysis to collect data that would allow for a closer identification of the consumer groups that are more accepting of this new technology and the reasons behind their acceptance. One limitation of this study is that we examined only a small number of quality attributes for table grapes, and future work could also expand this set to include a wider range of fruit quality and production attributes that are important to a wider range of consumers, grape producers, food retailers, and plant breeders.

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Table 1. List of attributes and options used in the choice experiment

Attributes	Options	
Fruit size Size of one grape berry	Smaller than a dime (less than ¾ inch)	Larger than a dime (more than ¾ inch)
Skin color Grape external color	100% green color	Green background with 50% amber/yellow blush color
Crispness Acoustic sensation detected by the ear during the fracturing of crisp foods	Crisp	Not crisp
Sweetness Taste related attribute: Perception of sweet is similar to the perception of acid, bitter, or salt	Not sweet	Sweet
Overall flavor Non-taste related attribute fruity, neutral floral, honey, perfumed, cotton candy	Fruity	Neutral
Price ($/lb)	1.98	2.98

Table 2. Model selection criteria for the latent class model

Classes	Number of Observations	Degrees of freedom	AIC[1]	BIC[2]
2	2,873	35	54,160	54,369
3	2,873	53	52,354	52,670
4	2,873	71	51,766	52,189

[1] AIC is Akaike Information Criterion
[2] BIC is Bayesian Information Criterion

Table 3. Demographic characteristics of survey respondents compared to U.S. Census, categorical variables

Item	Survey version 1 (N=1,422)	Survey version 2 (N= 1,451)	U.S. Census 2018
	Percentage of responses in each category		
Female	59.3	58.1	50.8
Race			
White/Caucasian, European American	76.7	74.1	76.3
Asian, Asian American	7.6	8.8	5.9
Black, African American	7.8	7.7	13.4
Hispanic or Latino American	6.2	6.8	18.5
American Indian or Alaskan Native	0.7	1.2	1.3
Pacific Islander	0.3	0.1	0.2
Other (Human, Mixed, Spain, Greek etc.)	0.4	0.6	-
Household annual income			
Less than $25,000	8.1	9.2	20.2
$25,000–$34,999	8.4	4.9	9.3
$35,000–$49,999	4.9	6.6	12.6
$50,000–$74,999	18.4	19.9	17.5
$75,000–$99,999	15.2	15.0	12.5
$100,000–$149,999	20.7	21.5	14.6
$150,000–$199,999	9.3	10.7	6.3
More than $200,000	10.1	8.6	7.0
Prefer not to answer	4.9	3.8	
Percent of families with children under 18 years	49.4	46.1	15.9
Place of residence			
Rural	18.8	17.1	
Urban	36.7	37.4	
Suburban	44.5	45.5	
Worked/Lived in a farm or ranch	28.1	24.0	
Vegetarian	19.5	14.3	

Table 4. Demographic characteristics of survey respondents compared to the U.S. Census, continuous variables

Item	Survey version 1 (N=1422)	Survey version 2 (N= 1451)	Difference: version1 – version 2 t-value[1]	U.S. Census 2018
Age (years)	42.2 (15.9)[3]	42.5 (15.9)	-0.4[2]	38.2
Household size (count)	2.9 (1.3)	2.9 (1.3)	0.8	2.6
Number of children under 18 per household (count)	0.8 (1.0)	0.8 (1.0)	0.7	
Household annual income (dollars/year)	97,514.4[4] (57,435.3)	97,379.6[4] (56,330.3)	0.1	84,938

[1] T-statistic for the difference between the two means in the previous two columns.
[2]*, **, *** indicates statistically significantly different from zero at the 10%, 5%, and 1% level.
[3] Standard deviations in parentheses.
[4] The mean household annual income was calculated based on a total number of respondents of 1,353 for survey version 1 and 1,396 for survey version 2. The reason for the difference in number of responses is an option of "Prefer not to answer" was included.

Table 5. Coefficient estimates for the mixed logit model, including selected table grape quality attributes and considering two different breeding methods

Variable	Means and standard deviations of coefficient estimates	
	Version 1 Conventional breeding	Version 2 Gene editing
	Mean coefficient	
Price	-0.35***[1] (0.03)[2]	-0.33*** (0.03)
Sweetness (not sweet vs. sweet)	0.66*** (0.04)	0.71*** (0.04)
Crispness (not crisp vs. crisp)	0.57*** (0.04)	0.46*** (0.04)
Flavor (neutral vs. fruity)	0.50*** (0.05)	0.40*** (0.05)
Color (50% amber vs. 100% green)	0.30*** (0.03)	0.30*** (0.04)
Size (smaller vs.larger than a dime)	0.23*** (0.05)	0.17*** (0.05)
Alternative specific constant—None option	-0.01 (0.08)	0.03 (0.08)
	Standard deviation of coefficients	
Sweetness (not sweet vs. sweet)	0.77*** (0.05)	1.01*** (0.05)
Crispness (not crisp vs. crisp)	0.65*** (0.05)	0.76*** (0.05)
Flavor (neutral vs. fruity)	0.92*** (0.06)	0.95*** (0.06)
Color (50% amber vs. 100% green)	0.43*** (0.06)	0.53*** (0.06)
Size (smaller vs. larger than a dime)	0.97*** (0.05)	0.99*** (0.05)
No. of observations	34,128	34,824
Log likelihood	-11,692.11	-11,822.72

[1] *, **, *** indicates statistically significant at the 10%, 5%, and 1% level.
[2] Standard errors in parenthesis.

Table 6. Bootstrapped WTP estimates and confidence intervals for selected table grape attributes

	Willingness to pay estimates ($/lb)		
	Version 1 Conventional breeding	Version 2 Gene editing	Difference in WTP: version 1 – version 2 t-value[1]
Sweetness (not sweet vs. sweet)	1.86 [1.79, 1.93][2]	2.18 [2.07, 2.30]	-4.89***[1]
Crispness (not crisp vs. crisp)	1.61 [1.56, 1.66]	1.41 [1.342, 1.479]	4.60***
Flavor (neutral vs. fruity)	1.41 [1.33, 1.50]	1.22 [1.13, 1.31]	3.11***
Color (50% amber vs. 100% green)	0.84 [0.82, 0.87]	0.93 [0.89, 0.97]	-3.89***
Size (smaller vs. larger than a dime)	0.65 [0.55, 0.73]	0.51 [0.42, 0.62]	1.82*
Aggregated table grape	2.12 [2.05, 2.19]	2.09 [2.00, 2.18]	0.58

[1] *, **, *** indicates statistically significant at the 10%, 5%, and 1% level.
[2] 95% confidence intervals.

Table 7. Coefficient estimates for the latent class model considering the aggregated WTP for table grapes developed using conventional breeding

	Mean			ANOVA p-value		
	Class 1 Little knowledge	Class 2 Some knowledge	Class 3 Large knowledge	Class 1 vs Class 2	Class 1 vs Class 3	Class 2 vs Class 3
Mean calculated WTP ($/lb)	1.76 (1.49)[1]	2.07 (1.38)	2.54 (1.13)	0.002	0.000	0.000
Percentage of respondents in each class (N=1,422)	0.27	0.44	0.29			
Male (%)	0.36 (0.48)	0.27 (0.44)	0.66 (0.48)	0.005	0.000	0.000
Millennial (%) (born after 1980)	0.49 (0.50)	0.43 (0.50)	0.66 (0.47)	0.212	0.000	0.000
Income above or equal 100K	0.31 (0.46)	0.36 (0.48)	0.54 (0.50)	0.318	0.000	0.000
Households with children<18 (%)	0.40 (0.49)	0.36 (0.48)	0.78 (0.42)	0.412	0.000	0.000
Household size >= 5 median (%)	0.10 (0.29)	0.11 (0.31)	0.16 (0.37)	1.000	0.011	0.020
Consume at least once/week (%)	0.03 (0.17)	0.01 (0.08)	0.15 (0.35)	0.353	0.000	0.000
Importance of source of information						
Friends/family (%)	0.55 (0.50)	0.74 (0.44)	0.90 (0.30)	0.000	0.000	0.000
Government agencies (%)	0.25 (0.44)	0.69 (0.46)	0.84 (0.37)	0.000	0.000	0.000
Medical professionals (%)	0.36 (0.48)	0.87 (0.33)	0.91 (0.28)	0.000	0.000	0.275
Media (%)	0.13 (0.34)	0.25 (0.43)	0.81 (0.39)	0.000	0.000	0.000
Social media (%)	0.08 (0.27)	0.12 (0.32)	0.78 (0.42)	0.173	0.000	0.000
Science journal (%)	0.07 (0.26)	0.88 (0.33)	0.81 (0.40)	0.000	0.000	0.003
Scientific association (%)	0.05 (0.23)	0.96 (0.21)	0.83 (0.38)	0.000	0.000	0.000
Perceptions of breeding methods, percentage of respondents						
Know about gene editing	0.19 (0.39)	0.25 (0.43)	0.83 (0.37)	0.060	0.000	0.000
Consider gene editing as safe to eat	0.21 (0.41)	0.33 (0.47)	0.85 (0.36)	0.000	0.000	0.000
Consider gene editing as natural	0.16 (0.37)	0.12 (0.32)	0.85 (0.36)	0.149	0.000	0.000
Consider gene editing as ethical	0.19 (0.39)	0.26 (0.44)	0.89 (0.32)	0.028	0.000	0.000

[1] Standard deviation in parentheses.

Table 8. Coefficient estimates for the latent class model considering the aggregated WTP for table grapes developed using gene editing

	Mean			ANOVA p value		
	Class 1 Little knowledge	Class 2 Some knowledge	Class 3 Large knowledge	Class 1 vs Class 2	Class 1 vs Class 3	Class 2 vs Class 3
Mean calculated WTP ($/lb)	1.72	1.92	2.76	0.166	0.000	0.000
	(1.91)[1]	(1.81)	(1.36)			
Percentage of respondents in each class (N=1,422)	0.30	0.43	0.27			
Male (%)	0.38	0.30	0.65	0.012	0.000	0.000
	(0.49)	(0.46)	(.48)			
Millennial (%) (born after 1980)	0.52	0.43	0.64	0.012	0.001	0.000
	(0.50)	(0.50)	(.48)			
Income above or equal 100K	0.31	0.35	0.61	0.433	0.000	0.000
	(0.46)	(0.48)	(0.49)			
Households with children<18 (%)	0.39	0.34	0.73	0.393	0.000	0.000
	(0.49)	(0.48)	(0.45)			
Household size >= 5 median (%)	0.10	0.09	0.15	1.000	0.040	0.008
	(0.29)	(0.29)	(0.36)			
Consume at least once/week (%)	0.03	0.003	0.16	0.158	0.000	0.000
	(0.17)	(0.06)	(0.37)			
Importance of source of information						
Friends/family (%)	0.48	0.73	0.87	0.000	0.000	0.000
	(0.50)	(0.44)	(0.33)			
Government agencies (%)	0.25	0.66	0.86	0.000	0.000	0.000
	(0.43)	(0.47)	(0.35)			
Medical professionals (%)	0.35	0.87	0.91	0.000	0.000	0.507
	(0.48)	(0.33)	(0.29)			
Media (%)	0.10	0.27	0.81	0.000	0.000	0.000
	(0.30)	(0.45)	(0.40)			
Social media (%)	0.10	0.14	0.79	0.312	0.000	0.000
	(0.30)	(0.34)	(0.41)			
Science journal (%)	0.10	0.88	0.84	0.000	0.000	0.232
	(0.30)	(0.33)	(0.37)			
Scientific association (%)	0.07	0.94	0.85	0.000	0.000	0.000
	(0.26)	(0.23)	(0.36)			
Perceptions of breeding methods, percentage of respondents						
Know about gene editing	0.19	0.21	0.89	1.000	0.000	0.000
	(0.39)	(0.41)	(0.31)			
Consider gene editing as safe to eat	0.19	0.33	0.88	0.000	0.000	0.000
	(0.39)	(0.47)	(0.33)			
Consider gene editing as natural	0.16	0.11	0.86	0.096	0.000	0.000
	(0.36)	(0.31)	(0.35)			
Consider gene editing as ethical	0.16	0.28	0.88	0.000	0.000	0.000
	(0.36)	(0.45)	(0.33)			

[1] Standard deviation in parentheses.

Appendix A.

Each table grape variety was developed using one of the following breeding techniques: Conventional breeding and gene editing (e.g. CRISPR)

- **Conventional breeding**: Plants with desirable traits are bred together, using existing varieties or the offspring of previous breeding programs that have the desired traits. This results in hundreds of potentially desirable plants that must be whittled down to the best candidates for commercial use. May be labelled as organic (if other production requirements are satisfied) or GMO-free.

- **Gene editing (e.g. CRISPR)**: Specific genes can be altered, without introducing genes from any other sources. Similar to editing a word in a novel, gene editing can target specific DNA sequences in the genome for slight modification, which can improve plant traits. The USDA recently proposed that plants produced using gene editing will be treated the same as conventionally bred plants. For this study we can assume grapes produced using gene-editing may be labeled as organic (if other production requirements are satisfied) or GMO-free.

Figure 1. Explanation of the plant breeding technologies provided to survey respondents.

Table B1. Frequency distribution of respondents describing table grape consumption features

Table grape consumption features	Survey version 1 (N = 1422)	Survey version 2 (N = 1451)
	Percentage of responses in each category	
Consumption frequency		
1–2 times per week	19.8	20.6
3–4 times per week	7.8	8.3
4 or more times per week	5.3	5.5
Every 2–3 weeks	35.4	35.8
Every 2–3 months	20.9	21.6
2–3 times per year	8.8	5.9
Less than 2 times per year	2.0	2.2
Reason for not consuming more often	N=450	N=431
Availability/access to table grapes	17.8	20.9
Don't like the external appearance	2.7	3.7
Don't like the flavor	11.6	3.7
Don't like the texture	2.0	3.9
Have a preference for other fruit	30.4	33.9
Preparation time (i.e., washing)	2.7	2.1
Too expensive	25.3	20.7
Other (Spoil fast, variety etc.)	7.6	11.1
Preferred table grape package		
Clamshell	26.0	21.6
Pre-bagged	57.5	59.8
Loose	16.5	18.6
Type of table grape often bought		
Black	7.5	8.8
Red	40.7	43.5
Green	48.5	47.3
Other (Mix, unsure etc.)	3.3	0.5

Table B2. Rating of importance assigned to table grape traits and pairwise t-test comparison across survey versions

Table grape traits	Survey version 1 (N = 1422)	Survey version 2 (N = 1451)	Difference in version 1 – version 2 t-value[1]
	Mean (Standard deviation) Scale 1-5: 1=very unimportant, 5=very important		
Uniform and attractive berry color	3.9	3.9	0.34
	(1.0)[2]	(1.0)	
Specific fruit size (large, medium, small berries)	3.7	3.7	-0.96
	(1.0)	(1.0)	
Berries appear free from defects (brown spots, cracks, etc.)	4.2	4.3	-0.99
	(1.0)	(0.9)	
Stems appear green rather than dried out	3.8	3.8	-0.49
	(1.0)	(1.0)	
Berries are of uniform size and shape	3.6	3.6	-0.57
	(1.1)	(1.0)	
Thickness of berry skin	3.6	3.6	0.67
	(1.0)	(1.0)	
Seed lessness	4.2	4.2	-0.06
	(1.0)	(1.0)	
Freshness	4.5	4.5	-0.33
	(0.9)	(0.8)	
Ripeness	4.3	4.3	0.08
	(0.9)	(0.9)	
Crispness	4.2	4.1	0.72
	(1.0)	(0.9)	
Firmness	4.2	4.2	-0.32
	(0.9)	(0.9)	
Juiciness	4.3	4.3	-0.09
	(0.9)	(0.9)	
Unique flavor (e.g., cotton candy)	3.3	3.3	0.57
	(1.3)	(1.3)	
Aroma	3.5	3.5	-1.63
	(1.1)	(1.1)	
Tartness (acidity)	3.5	3.5	-0.07
	(1.1)	(1.0)	
Sweetness	4.2	4.2	0.28
	(0.9)	(0.9)	
Phytonutrient content (e.g., vitamins, antioxidants)	3.8	3.8	0.14
	(1.0)	(1.0)	

[1] t-statistic for the difference between the two means in the previous two columns.
[2] Standard deviations in parentheses.

Table B3. Respondents' rating of importance of different food labels, and pairwise t-test comparison across survey versions

Food label	Survey version 1 (N = 1422)	Survey version 2 (N = 1451)	Difference in: version 1 – version 2 t-value[1]
	Mean (Standard deviation) Scale 1-5: 1=totally irrelevant, 5=crucial		
A private brand	2.8 (1.6)[2]	2.8 (1.6)	0.07
Local origin	3.3 (1.4)	3.3 (1.3)	-0.84
Domestic product	3.5 (1.3)	3.5 (1.2)	-0.78
Name of the grape variety	3.2 (1.4)	3.1 (1.3)	1.27
Seedless	4.1 (1.2)	4.0 (1.1)	0.69
Organic	3.3 (1.4)	3.2 (1.4)	0.75
Sustainable agriculture	3.3 (1.4)	3.4 (1.3)	-0.38
Non-GMO	3.4 (1.5)	3.4 (1.4)	-0.04
Eco-label	3.4 (1.4)	3.4 (1.4)	-0.14
Pesticide free	3.8 (1.3)	3.8 (1.3)	-0.19

[1] t-statistic for the difference between the two means in the previous two columns.
[2] Standard deviations in parentheses.

Table B4. Respondents' rating of importance assigned to the trustworthiness of sources of information and pairwise t-test comparison across survey versions

Source of information	Survey version 1 (N = 1422)	Survey version 2 (N = 1451)	Difference in: version 1 – version 2 t-value[1]
	Mean (Standard deviation) Scale 1-5: 1=strongly do not trust, 5=strongly trust.		
Activist groups (e.g., Green America)	3.4	3.3	1.08
	(1.1)[2]	(1.1)	
Consumer organizations (e.g., American Council of Consumers Interests)	3.6	3.6	1.04
	(1.0)	(1.0)	
Individual farmers	4.1	4.0	2.31**
	(0.9)	(0.9)	
Farmer organizations (e.g., California Table Grape Commission)	3.9	3.8	0.68
	(0.9)	(0.9)	
Food manufacturers (e.g., Nestle, General Mills)	3.5	3.4	0.84
	(1.1)	(1.2)	
Food retailers (e.g., Walmart)	3.5	3.5	-0.17
	(1.1)	(1.1)	
Friends, family members	4.1	4.0	2.93***
	(0.9)	(0.9)	
Government agencies (e.g., USDA, FDA)	3.7	3.6	1.71*
	(1.1)	(1.1)	
Medical professionals	4.1	4.0	1.97**
	(0.9)	(1.0)	
Media	3.1	3.0	1.19
	(1.2)	(1.2)	
Social media	2.8	2.8	-0.36
	(1.3)	(1.3)	
Science journals (e.g., Nature) and blogs	3.8	3.7	0.33
	(1.0)	(1.0)	
Scientific association (e.g., American Association for the Advancement of Science)	3.8	3.8	0.30
	(1.0)	(1.0)	
Local government	3.4	3.4	1.12
	(1.1)	(1.1)	
Universities	3.7	3.7	1.13
	(1.0)	(1.0)	

[1] t-statistic for the difference between the two means in the previous two columns.

[2] Standard deviations in parentheses.

Table B5. Respondents' rating of importance assigned to perceptions on breeding methods, and pairwise t-test comparison across survey versions

	Survey version 1 (N = 1422)	Survey version 2 (N = 1451)	Difference in: version 1 – version 2 t-value[1]
	Mean (Standard deviation)		
How informed respondents are on breeding methods (1=completely uninformed, 5=completely informed)			
Conventional breeding	3.2	3.2	0.43
	(1.3)[2]	(1.2)	
Gene editing	3.0	3.0	0.14
	(1.3)	(1.2)	
Genetic engineering	3.3	3.2	0.38
	(1.3)	(1.2)	
Level of risk perceived (1=highly risky to eat, 5=totally safe to eat)			
Conventional breeding	3.9	3.8	1.38
	(1.0)	(1.0)	
Gene editing	3.3	3.3	0.62
	(1.1)	(1.1)	
Genetic engineering	3.2	3.2	0.82
	(1.2)	(1.2)	
Conventional farming	4.1	4.1	1.55
	(0.9)	(0.9)	
Organic farming	4.4	4.3	1.83*
	(0.9)	(0.9)	
How natural the methods are (1=highly unnatural, 5=completely natural)			
Conventional breeding	3.8	3.7	2.09**
	(1.0)	(1.1)	
Gene editing	2.9	2.9	0.31
	(1.3)	(1.2)	
Genetic engineering	2.8	2.7	0.32
	(1.3)	(1.3)	
Conventional farming	4.1	4.0	1.59
	(0.9)	(0.9)	
Organic farming	4.3	4.2	2.28**
	(0.9)	(0.9)	
How ethical or morally acceptable the methods are (1=completely unethical, 5=completely ethical)			
Conventional breeding	3.8	3.8	1.31
	(1.1)	(1.1)	
Gene editing	3.3	3.2	0.92
	(1.2)	(1.1)	
Genetic engineering	3.1	3.1	-0.22
	(1.3)	(1.2)	
Conventional farming	4.1	4.1	1.38
	(0.9)	(1.0)	
Organic farming	4.4	4.3	1.88*
	(0.9)	(0.9)	

[1] t-statistic for the difference between the two means in the previous two columns.
[2] Standard deviations in parentheses.