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RESEARCH ARTICLE

Would consumers accept CRISPR fruit crops if the benefit has health implications? An application to cranberry products

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Abstract

Cranberry products are perceived as healthy due to their high antioxidant content yet adding sugars to increase their palatability deters consumption. Plant breeding technologies such as gene editing, specifically the clustered regularly interspaced palindromic repeats (CRISPR), offer a plausible alternative to develop cranberries with desired traits (e.g., lower acidity and increased sweetness). We estimated consumers' willingness to pay for sugar content, CRISPR, and cranberry flavor intensity for two cranberry products under different health-related information treatments. Respondents stated a discount for regular sugar content favoring reduced sugar products, for CRISPR compared to conventional breeding, and for weak/bland compared to full/intense cranberry flavor. Compensated valuation analysis of products with different attribute levels indicates that consumers were willing to pay a premium for cranberry products with reduced sugar content, CRISPR-bred, and full/intense cranberry flavor relative to products with regular sugar content, conventionally bred, and weak/bland flavor. Information treatments highlighting cranberries' health benefits and recommendations to limit sugar intake increased consumers' discounts for regular sugar content, surpassing the discount for CRISPR. This research underscores the importance of the conditions under which breeding technologies might gain public acceptance. This information will benefit the scientific community and industry seeking to use CRISPR to develop improved cranberry cultivars.

Keywords: CRISPR; processed fruits; consumer acceptance; health and nutrition

JEL classification: Q13; Q16

Introduction

Gene editing is a relatively new breeding technology with increasing applications since its development in the 2010s. This technology targets and controls a specific genome portion without inserting foreign DNA into the host organism (Doudna and Charpentier 2014). Among gene editing technologies, clustered regularly interspaced palindromic repeats–Cas9 (hereafter CRISPR) is the most commonly used method due to its reduced cost, enhanced efficiency, and relative ease of use (Critchley et al. 2018). Since its introduction, the application of this technology has been tested in several areas of biological research and model systems, including human disease discovery and treatments, food processing, and crop improvement (Hall 2016; Haspel 2018).

Scientific research on CRISPR applications in agriculture is abundant. Findings have shown improvements in crop quality attributes, agronomic traits, and climate stress tolerance in multiple crops (Menz et al. 2020; Zhang et al. 2018). In this study, we investigate whether consumers would perceive gene editing as another iteration of genetic modifications with unpredictable consequences to human health and the environment, similar to their views on genetic engineering[1] applications to agriculture.

New plant breeding technologies, specifically genetic engineering, have scientifically proven contributions to agricultural crops. After three decades of scientific research and commercial applications of genetic engineering in agriculture, there is no proof of an increased risk to either human health or the environment compared to conventionally bred crops (Qaim 2020). Despite the scientific evidence, food manufacturers and retailers shared the expectation that consumers would respond negatively to genetic engineering applications in foods (Kalaitzandonakes, Lusk and Magnier 2018). The lack of wide public acceptance of genetic engineering applications in agriculture hindered the full realization of potential benefits (Alston and Pardey 2021). However, the literature also shows that genetically engineered products exhibit the largest market share (60%) for specific food categories, such as salads and cooking oils (Kalaitzandonakes, Lusk and Magnier 2018).

Cranberries offer an interesting case for investigating the trade-off between health-related attributes in agricultural products demanded by consumers and the application of new breeding technologies. Cranberries are high in acidity and contain low amounts of natural sugars. Therefore, the industry must add regular sugar or sugar naturally occurring in other fruits to improve the palatability of processed cranberry products, thus giving the perception that the total sugar content is higher compared to other fruit juices, when this is not necessarily the case. The high anthocyanin and proanthocyanidin content of cranberries has been proven to positively affect human health, juxtaposing with added sugar's perceived negative health effects. A plausible solution is to develop cranberry cultivars using gene editing technology or traditional breeding that either have lower acid content or high natural sugars and retain their anthocyanin and proanthocyanidin content. There is also an increased interest in the development of genetic markers for cranberries associated with sugars and phytochemicals to facilitate breeding with other species of the genus *Vaccinium,* such as wild cranberries, lingonberries, deer berries, even certain blueberries that are cross-compatible with cranberries and possess an array of phytochemicals and other traits with high agronomical value. The aim is to develop cranberry varieties with enhanced quality for processing and human nutrition and improved palatability.

[1]In this study, we use genetic engineering to refer to the use of recombinant DNA technologies to alter the genetic sequence of an organism and to create a transgenic organism, that contains genome consisting of DNA sequences from a different species (Entine et al., 2021). In the survey conducted in this study, we used the terminology GMO – genetically modified organisms, because it is the terminology most known to the public. When reporting results from the survey, we used the term GMO otherwise we refer to genetic engineering.

The cranberry products included in this study were selected for their importance in the cranberry industry, as measured by their sales volume. In the United States, 95% of the cranberries grown are processed and 5% are sold fresh (Agricultural Marketing Resource Center 2023). The major volume in the U.S. domestic market is for juices and sweetened dried cranberries. According to the largest cooperative of cranberry growers in the United States, on average 70–75% of the fruit is processed into juice and sweetened dried cranberries, 12–18% is processed into juice only, 4–6% is processed into sauce, and 3–5% is sold as fresh cranberries (R. Serres, personal communication, 31 May 2023).

The "unhealthy" perception of "Added sugars" is amplified by the recent U.S. Food and Drug Administration (FDA) labeling rule requiring products to explicitly report "Added Sugars" on the Nutrition Facts Panel (NFP) in addition to the "Total Sugar" content. Previous studies have found that consumers often misinterpret the information on "Added Sugar" and "Total Sugar" on the NFP of packaged products (Kim et al. 2021b; Laquatra et al. 2015; Tierney et al. 2017; Khandpur, Rimm and Moran 2020). Studies analyzing the new "Added Sugar" labeling mandate have found no effects of the labeling on purchase behavior (Neuhofer et al. 2020). Other studies found that individuals' self-perceived healthy lifestyles positively influenced the labeling effects on purchase behavior (Kim et al. 2021a; Fang et al. 2019).

Literature states that consumers' perception of genetic engineering is influenced by information available, prior knowledge, perceived risks and benefits, and individual characteristics (Hu, House and Gao 2022; Uddin et al. 2022). Focusing on the effects of information, studies have analyzed different aspects, such as narrative style when presenting the information (Yang and Hobbs 2020; McFadden et al. 2021); and the effects of trust on the sources of the information (Paudel et al. 2023). Studies centering on the effects of information explaining genetic engineering found that positive information increases acceptance of these methods (Lusk et al. 2004). And when both positive and negative information on genetic engineering is presented, the negative outweighs the effects of the positive information (Lee et al. 2018). Kilders and Caputo (2021) analyzed the effects of information centering on the results of applying gene editing technology, in this case, to breed cows with no horns, improving animal welfare. They found that when information highlighting the enhancement of animal welfare acceptance of both conventional and gene-edited dehorned cows increased. Also, that information increased the preference distributions, implying that information had a heterogeneous impact on preferences.

This study has four objectives. First, we estimate consumers' willingness to pay (WTP) for CRISPR versus conventional breeding in dried cranberries and cranberry juice. Second, given the importance of information on accepting a novel breeding technology, we center on the effects of information – highlighting the health benefits of consuming cranberries and the effects of sugar intake on diets – on consumers' WTP for CRISPR-bred cranberries. Third, we conduct a welfare analysis on the potential impact of using CRISPR. Finally, we assess differences in WTP for cranberry product attributes across respondent segments.

The contribution of this study is to advance knowledge on the public's acceptance of CRISPR, a relevant topic considering its exponential growth in the agri-food industry. The scientific community and agricultural stakeholders should know which crop improvements would enhance public acceptability or mitigate the rejection of CRISPR. To our knowledge, there are no studies investigating the application of gene editing to improve palatability or enhance the healthfulness of a product. That is, whether consumers would be more receptive to CRISPR when its application results in a cranberry product that is perceived to be healthier as it exhibits reduced total sugars or no added sugars. Given the potential of CRISPR technology, applying CRISPR to cranberries is plausible.

This study also aims to fill the gap in understanding how various information treatments regarding recommendations to limit added sugars and the health benefits of cranberries could affect the WTP for total sugars and the trade-offs between reduced sugar content and CRISPR.

About CRISPR labeling regulations in the U.S., there is a mix of guidelines from multiple agencies, suggesting that the extent of the gene-edited crop regulations will happen on a case-by-case basis (Parrott 2022). The U.S. Department of Agriculture-Animal and Plant Health Inspection Service (USDA-APHIS) approved the release of gene-edited organisms without further regulation only if it does not pose any plant or animal pest risk; beyond this, edited organisms are subject to regulatory status review (Entine et al. 2021). The U.S. Department of Agriculture-Agricultural Marketing Service (USDA-AMS) released the "National Bioengineered Food Disclosure Standard," stipulating that foods containing gene-edited ingredients would not be subject to disclosure, only if the ingredients do not come from crops involving novel DNA combinations that were created by other methods different from conventional breeding or found in nature (Entine et al. 2021). The Environmental Protection Agency (EPA) has shown the intention to regulate gene-edited plants that have a pesticidal property for pest resistance. The FDA released the "Plant and Animal Biotechnology Innovation Plan" to clarify their policies regarding food safety evaluations of foods containing ingredients from gene-edited crops (Entine et al. 2021).

Given that different labeling mandate scenarios for CRISPR foods are possible, we consider it informative for the scientific community and the agricultural industry to explore consumers' acceptability of CRISPR for two reasons. First, one issue differentiating CRISPR from genetic engineering is that it was developed by academia, and all information about the technology and its applications are being made public. Increased transparency around CRISPR, community involvement, and applications that benefit the public interest could help gain public acceptance and dissipate some of the concerns raised about genetic engineering (Hall 2016; Haspel 2018). Second, more applications in the food and fiber sector are likely to be available in the marketplace. CRISPR is more affordable and accessible to a wider variety of institutions and companies and is not exclusive to large multinational companies (Haspel 2018; Dewey 2018).

Literature review

There is abundant literature on consumers' WTP for genetically engineered crops with a consistent finding: consumers are willing to pay price premiums to avoid foods that use ingredients from genetically engineered plants and animals (Lusk et al. 2005; Dannenberg 2009). When comparing discounts across different food products, consistently, consumers applied a larger discount for genetically engineered fresh foods than for genetically engineered processed foods (Lusk, McFadden and Rickard 2015). When studying the effects of labeling, a study found that the presence of "genetically engineered" labels boosted the demand for unlabeled apples, strawberries, and potatoes (Yeh, Gomez and Kaiser 2019).

Previous studies analyzing consumers' WTP for foods from gene-edited crops have found that individuals were willing to discount less for gene-edited foods than genetically engineered foods, with some exceptions (Hu, House and Gao 2022). However, both gene-edited and genetically engineered plants and animals experienced a discount compared with their conventionally bred counterparts (Shew et al. 2018; An, Lloyd-Smith and Adamowicz 2019; Muringai, Fan and Goddard 2020; Yang and Hobbs 2020; Marette, Disdier and Beghin 2021; Kilders and Caputo 2021). Shew et al. (2018) found that respondents were more willing to consume gene-edited compared to genetically engineered rice.

However, their sample of respondents stated a discount for genetically engineered and gene-edited rice compared to the conventionally bred product. An, Lloyd-Smith and Adamowicz (2019) found that their respondents were willing to pay a price premium for gene-edited relative to genetically engineered canola oil. Yang and Hobbs (2020) and Marette, Disdier and Beghin (2021) concluded that their respondents were willing to discount both gene-edited and genetically engineered apples. However, the discount for gene-edited was smaller than the discount for genetically engineered apples. Muringai, Fan and Goddard (2020) found that respondents stated a discount for frozen French fries produced using genetically engineered and gene-edited compared to conventionally bred potatoes. Still, the discount for gene-edited was smaller than that for genetically engineered potatoes.

On the effects of information, Kilders and Caputo (2021) found that information about the potential to use CRISPR to enhance animal welfare positively affected the WTP for milk from cows that have been gene-edited to prevent painful dehorning. Hu, House and Gao (2022) found no differences between the WTP of CRISPR and genetically engineered orange juice. However, with information on how each technology works, the WTP for both technologies increased. McFadden et al. (2021) found that both positive – linking gene editing with conventional breeding – and negative – linking gene editing with genetic engineering – messaging strategies led to similar discounts for gene editing and genetic engineering. Paudel et al. (2023) found that survey respondents exhibited greater preference and WTP for gene-edited foods developed by domestic startups and universities than multinational firms. They also found that communicating gene-edited crops' health and environmental benefits enhanced respondents' acceptance.

Overall, studies show that the extent of the acceptance of gene editing over genetic engineering depends, in part, on the nature of the innovation and, thus, the benefit perceived by the consumer. As agriculture faces a changing production environment, increasing global consumer demand, and consumer demand for healthier products, the future food supply will largely depend upon the development and application of technologies such as genome editing to ensure global food demand is met (Voytas and Gao 2014; Qaim 2020; Nes, Schaefer and Scheitrum 2022).

Methods

Data collection – Experimental design

The data were collected via two online surveys – one for dried cranberries and another for cranberry juice – administered by the Qualtrics Research Services™ consumer research panel. We asked Qualtrics to gather participants over 18 years of age through random selection, to match the demographic profile of gender, age, and income as closely as possible to the general population in the United States. The surveys were pretested during a soft launch in November 2020, and data collection took place from December 2020 through March 2021.

The survey consisted of eight versions originating from the combination of four information treatments and two products (dried cranberries and cranberry juice[2]).

[2]The cranberry juice survey version included two sets of discrete choice experiments (DCE), one centering on an "unlabeled/generic" juice, where the DCE presented three alternatives: Option A, Option B, and Option C (no-buy option). These alternatives did not distinguish the type of juice. The second set of DCE centered on "labeled" juice categories, where the DCE presented four alternatives: 100% juice, cocktail, juice blend, and the no-buy option. These later did distinguish between the three types of juice in the market. Findings from the unlabeled set are generally consistent with those for the labeled juice. To streamline the information presented in this manuscript, the "unlabeled" juice results are not reported but are available from the authors upon request.

Table 1. List of attributes and attribute levels for sets of discrete choice experiment scenarios for dried cranberries, and cranberry juice

	Alternative possibilities available for each attribute	
Attributes	Dried cranberry survey version	Cranberry juice survey version
Total sugars (per serving size 1 cup)	• 29 g • 14 g	• 25 g • 12 g
Cranberry flavor	• Full/intense • Bland/weak	• Full/intense • Bland/weak
Cranberry breeding technology	• Conventional breeding • Gene editing	• Conventional breeding • Gene editing
Price	• $1.99/6–oz bag • $2.99/6–oz bag • $3.99/6–oz bag	• $2.49/64–fl-oz bottle • $2.99/64–fl-oz bottle • $3.49/64–fl-oz bottle

Qualtrics provided 250 nationwide respondents for each survey version, resulting in 1,000 responses for the dried cranberry survey and 1,000 for the cranberry juice survey, totaling 2,000 respondents. The screening criteria for the respondents varied based on the product being surveyed. The dried cranberry survey aimed to gather responses from both regular and non-regular consumers, so individuals who purchased or consumed dried cranberries at least once a year were selected. For the cranberry juice survey, the study screened for individuals who were familiar with the different cranberry juice categories (100% cranberry juice, cranberry cocktail, and cranberry juice blend), as knowledge and experience with the product are necessary to mimic a real-life purchasing situation as closely as possible to provide accurate and unbiased estimates (Louviere, 2006). The Institutional Review Board approved the survey (Mississippi State University IRB-20-305).

Choice experiment design

This study used a discrete choice experiment (DCE) to elicit consumers' WTP for attributes of dried cranberries and cranberry juice. We used a cheap talk script (Champ, Moore and Bishop 2009) and a certainty scale to mitigate hypothetical bias (Hensher et al., 2012). The cheap talk script was presented to respondents in the explanation that preceded the DCE scenarios. An example of the complete set of descriptions presented to respondents is provided in Appendix A for dried cranberries and Appendix B for cranberry juice.

After each DCE scenario, a follow-up certainty question was presented following Hensher, Rose and Beck (2012) who proved that including questions to assess the extent to which a respondent is certain of actually choosing the DCE alternative mitigates the proneness to hypothetical bias. This study used the 1–10 certainty scale, where 1 = "Very uncertain" and 10 = "Very certain." An example of the certainty scale used is also included in Appendices A–B.

A detailed description of the attributes and attribute levels included in both DCE versions (dried cranberries and cranberry juice) is presented in Table 1. The study included three attributes with two levels: total sugars, cranberry flavor, and cranberry breeding technologies. A description of each attribute was included in the survey, before the DCE, and can be found in Appendix A for dried cranberries and Appendix B for cranberry juice. The total sugar levels for the dried cranberries were presented as "Regular" and "50 Less Sugar" which are equivalent to 29 g. and 14 g. of sugars per serving, respectively. For cranberry juice, "Original" is equivalent to 25 g., and "50% Less Sugar" is equivalent to 12 g. of sugars. These levels were aligned with commercial products in the market. Instead of added sugar, total sugar was included because the study aimed to investigate if there were trade-offs between total sugar content and the possibility of reducing it by applying CRISPR. By doing so, it is possible that the flavor intensity of cranberries is affected. Given that literature suggests flavor attributes are crucial for consumers' acceptance, we included flavor with two levels, full/intense and bland/weak. Price was included with three levels for each product. For dried cranberries: \$1.99, \$2.99, and \$3.00 per 6-oz bag, and for juice: \$2.49, \$2.99, and \$3.99 per 64-fl-oz bottle. These prices were consistent with prices of similar commercial products when the survey took place.

The attribute levels included yielded a total of 72 possible combinations ($2^3 \times 3^2$) for each cranberry product. We generated a multinomial logit D-efficient fractional factorial experimental design with no priors in NGENE version 1.2. The experimental design, for each cranberry product, consisted of 18 choice sets divided into three blocks of six choice tasks each, with a D-error of 0.06 and 0.23 for the dried cranberries and cranberry juice, respectively.

In the dried cranberries survey, respondents evaluated six hypothetical purchase scenarios. Each scenario consisted of two 6–oz bags of dried cranberries with varying attribute levels options (A and B) and a no-buy option. An example of a dried cranberries choice scenario is presented in Appendix A. For the cranberry juice version, respondents were presented with six scenario choices with three cranberry juice options – "100% Juice," "Cocktail," and "Blend" – and a no-buy alternative. The narrative that preceded the juice DCE had a definition of each juice type following guidance from industry stakeholders. An example of the cranberry juice scenario choice is presented in Appendix B.

Information treatments

Because the public is often exposed to different types of food information that could affect food preferences (Dutriaux et al. 2021), we tested how emphasizing different kinds of information scripts would impact the WTP for total sugars, flavor intensity, and plant breeding technology. We included four information treatments. Treatment 1 was the control, with no information.

Treatment 2 presented a script on the health benefits of cranberries: *Cranberries are considered a superfood due to their high nutrient and anthocyanin content. Anthocyanins are substances that can prevent or slow damage to cells caused by free radicals. The anthocyanin properties of cranberries provide multiple health benefits, including the support of cardiovascular health and reduction of the risk of some cancers.* We hypothesize that the treatment 2 information would result in a higher WTP (decreased price discount) for regular sugar content, CRISPR breeding, and bland and weak cranberry flavor, compared to the control: H_{01}: $WTP^{treatment1} \leq WTP^{treatment2}$, H_{a1}: $WTP^{treatment1} > WTP^{treatment2}$.

Treatment 3 presented a script with the recommended sugar intake limit and the benefit of limiting sugar consumption: *The FDA defines "Added Sugars" as sugars that are added during the processing of foods. Added sugars increase calories without contributing important nutrients. The Dietary Guidelines for Americans recommend limiting the daily amount of added sugars consumed to no more than 10% of total calories per day (which is equivalent to 200 calories or 50 grams per day). Diets lower in sugar-sweetened foods are* *associated with a reduced risk of developing cardiovascular disease*[3]. We anticipate that the inclusion of the information in treatment 3 would lead to a lower WTP (increased price discount) compared to the control, for regular sugar content, CRISPR breeding, and bland and weak cranberry flavor: H_{02}: $WTP^{treatment1}\quad WTP^{treatment3}$, H_{a2}: $WTP^{treatment1} < WTP^{treatment3}$.

Treatment 4 included both sets of information provided in treatments 2 and 3. In this case, we expect that the health benefits information will counterbalance the impact of the dietary recommendation to limit added sugar consumption, resulting in the same willingness to pay as in the control (H_{03}: $WTP^{treatment1} = WTP^{treatment4}$, H_{a3}: $WTP^{treatment1} \neq WTP^{treatment4}$).

The text describing each information treatment was presented right before the DCE. An example of Treatment 4, which includes both treatments 2 and 3 scripts, is shown right before the DCE exhibits in Appendices A for dried cranberries and B for cranberry juice. A between-subjects design was used for all survey versions. Respondents were randomly assigned to each information treatment.

The survey included questions about respondents' sociodemographic characteristics such as gender, age, racial-ethnicity, education, income, number of people in the household, presence of children, self-reported health status, and diet-related chronic disease diagnoses. The survey also included questions to gauge preferences for cranberry product attributes, food purchase habits, and respondents' use of NFP labels, use of information on the NFP label, and a heat map for respondents to identify the piece of information on the NFP most important to them. In addition, we included questions to measure whether respondents correctly interpreted the added sugar line on the NFP. We also asked questions to assess perceptions on using new technologies for food production and processing, plant breeding technologies (specifically genetic engineering versus CRISPR), and the level of trust on different information sources related to food.

Empirical approach

The current study's empirical approach stems from the demand theory by Lancaster (1966) and the random utility model by McFadden (1974) The demand theory states that consumers derive utility from the attributes inherent to a good rather than the good itself. At the same time, the random utility model postulates that consumers' utility can be explained by a deterministic component given by the good's attributes and a random component given by unobserved factors.

[3]Note here that the study focuses on consumers' preference for total sugar content in cranberry products and the health information treatment explains the recommendation to limit added sugars, not total sugars. We chose this path for a couple of reasons. First, we based our health information treatment on recommendations found in the Dietary Guidelines for Americans (U.S. Department of Agriculture, Dietary Guidelines for Americans, 2020), which provide recommendations to limit calories from added sugars and avoid foods and beverages with added sugars, but do not include recommendations for total sugars. Second, information on added sugars is important given the new FDA's labeling rule requiring products to explicitly report added sugars on the NFP in addition to the total sugar content. Most of the sugars in dried cranberries and juice cocktails come from added sugars, as cranberries have minimal naturally occurring sugars. Thus, while consumers tend to focus on total sugar content (Tierney et al., 2017; Rampersaud et al., 2014), with CRISPR there is a potential to develop varieties low in acid which would result in lower sugar content in the form of less sugars added to improve palatability. However, we acknowledge that based on how the information treatment was presented, we cannot disentangle how respondents reacted to this information as we could capture mixed total sugar and added sugar avoidance reactions.

This study estimated the models in WTP space using the Generalized Multinomial Logit Model (GMNL) proposed by Fiebig et al. (2010). The GMNL models allow for scale heterogeneity and preference heterogeneity. Scale heterogeneity is defined as the variance in the degree of randomness between respondents in the decision-making process. Following Fiebig et al. (2010), the general specification of the GMNL model is as follows,

$$U_{ni} = [\sigma_n \beta + \gamma \eta_n + (1-\gamma)\sigma_n \eta_n] x_{ni} + \varepsilon_{ni}$$

$$\beta_n = \sigma_n \beta + [\gamma + (1-\gamma)\sigma_n]\eta_n \tag{1}$$

where σ_n is the individual-specific scale of the idiosyncratic error term that captures scale heterogeneity and is log-normally distributed with mean $\bar{\sigma}$ and standard deviation τ. η_n is a vector of individual specific taste deviate from the mean based on observed attributes, and it captures residual preference heterogeneity, and γ is a parameter between 0 and 1 that controls how the variance of residual taste heterogeneity η_n varies with the scale heterogeneity σ_n.

We estimated the different model formulations encompassed by the GMNL: the Type II, where $\gamma = 0$ (GMNL-II) and Type I where $\gamma = 1$ (GMNL-I) to the Random Parameter Logit (RPL) model. In the GMNL-I model, the standard deviation of residual taste heterogeneity is independent of the scale, whereas in the GMNL-II model, it is proportional to the scale. The RPL model is a special case of the GMNL model where the scale of the error term, σ_n, is normalized to 1 (Fiebig et al. (2010). All models were estimated using the "gmnl" package in R 4.0.5 (Sarrias and Daziano 2017). After comparing goodness of fit indicators [Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the likelihood functions] of the models estimated, we found that the GMNL-II model outperforms the GMNL-I and RPL models. Thus, we report the results of the GMNL-II model.

Following the general form of the GMNL and the attributes of the cranberry products in our study, we can write the utility respondent n derives from choosing alternative I as:

$$\begin{aligned} U_{ni} = \beta_{ASC_n} ASC_n + \sigma_n(&-Price + \beta_{RS} RegularSugar + \beta_{BF} BlandFlavor \\ &+ \beta_{CRISPR} CRISPR + L\eta_n) + \varepsilon_{ni} \end{aligned} \tag{2}$$

where *Price* is a continuous variable that takes any of the three values in the experimental design, and whose coefficient takes a fixed value of −1. The coefficient of *Price* is normalized to −1 so that the attribute coefficients can be directly interpreted as WTP values (Sarrias and Daziano 2017). *RegularSugar* is a binary variable indicating the product has a regular sugar content, *BlandFlavor* is a binary variable indicating the product has a bland/weak cranberry flavor intensity (flavor was described as the overall combination of sensations and its influence by taste, aroma, look and texture), *CRISPR* is a binary variable indicating that the product is made from CRISPR cranberries, β_{ASC_n} is the alternative-specific constant (ASC), L is the lower triangular matrix of the Cholesky decomposition, and η_n follows a standard normal distribution.

We allowed for scale heterogeneity in the scale parameter σ_n across individuals based on their stated choice certainty level (Kunwar, Bohara and Thacher 2020), such that:

$$\sigma_n = exp(\delta certain_n + \tau \nu_n) \tag{3}$$

where δ is the parameter of the observed heterogeneity in the scale term, τ is the coefficient on the unobserved scale heterogeneity, $\nu_n \sim N(0,1)$, and $certain_n$ is an indicator variable

Table 2. Description of base cranberry product option and hypothetical option used in compensating surplus analysis

	Dried cranberries	Cranberry juice
Base option	A 6–oz bag of dried cranberries made from conventional-bred cranberries, regular sugar content, weak/bland cranberry flavor, priced at $2.99	A 64 fl-oz bottle of cranberry juice made from conventional-bred cranberries, regular sugar content, weak/bland cranberry flavor, priced at $2.99
Hypothetical option	A 6–oz bag of dried cranberries made from CRISPR-bred cranberries, reduced sugar content, full/intense cranberry flavor, priced at $2.99	A 64 fl-oz bottle of cranberry juice made from CRISPR-bred cranberries, reduced sugar content, full/intense cranberry flavor, priced at $2.99

equal to 1 if individual n's level of certainty after responding to each choice scenario is greater or equal to 7 and 0 otherwise.[4]

To investigate the trade-offs between having a product with regular sugar content and acceptance of CRISPR technology, we estimated the marginal rate of substitution between regular sugar content and CRISPR (see Appendix D).

Compensating surplus

To further understand respondents' preferences for cranberry products with different combination of attribute levels, we computed the compensating surplus (CS). This represents the welfare change for consumers when going from a base option to an improved hypothetical scenario. Following Britwum and Yiannaka (2019) and Espinosa-Goded, Barreiro-Hurlé and Ruto (2010), CS is defined as:

$$Compensating\ surplus = -\left(\frac{1}{\beta_{price}}\right)(V_1 - V_2)$$

where V_1 is the conditional indirect utility of the base option, V_2 is associated with the hypothetical option which represents the alternative with the change. The base option and hypothetical option are described in Table 2. The base option for both cranberry products (dried cranberries and cranberry juice) is defined as cranberry products manufactured from conventionally bred cranberries, with regular sugar content and a weak cranberry flavor. CRISPR-bred cranberries with reduced sugar content and full cranberry flavor are the hypothetical alternative. We solely used data from the control treatment (no additional information) group in order to rule out any potential impacts of the information treatment. In our GMNL-II certainty model, the parameter of *price* is fixed at −1, thus the economic surplus becomes:

$$Compensating\ surplus = V_1 - V_2 = \Delta\widehat{V}_l.$$

[4] 14.93%, 15.27%, 15.47%, and 11.67% of responses in treatment 1−4 have a certainty level less than 7 for the dried cranberries survey, respectively; 13.96%, 17.60%, 16.18%, and 19.02% of responses in treatment 1−4 have a certainty scale less than 7 for the cranberry juice survey.

Latent class model

A latent class analysis was performed to investigate the factors triggering the heterogeneity in WTP estimates for the cranberry products' attributes. The model assumes unobservable characteristics are captured by class membership variables or respondents' socioeconomic characteristics, cranberry and food purchase habits, knowledge, and perceptions of plant breeding methods (genetic engineering and CRISPR).[5]

The latent class model captures the heterogeneous preferences by identifying segments within the sample of survey respondents, namely classes. Accordingly, individuals were grouped into several latent classes or unobservable subgroups. Preferences across classes are heterogeneous, but choices within each class are homogeneous. The mathematical formulation of the latent class model can be found in (Greene and Hensher 2003)

To identify the number of classes, this study used a set of indicators including measures of goodness of fits such as AIC, BIC, and likelihood function; the best-fitting model is the one with the smaller AIC and BIC. Other criteria include the interpretability of results and classification diagnosis. The latter ensures that selected classes are not an expanded version of the other (Nylund-Gibson and Choi 2018). We opted for three classes across all regressions, as these models exhibit the lower values for the AIC and the BIC, ensuring the interpretability of results and the number of statistically significant parameter estimates in each class. Appendix D presents the measures of goodness of fit used as part of the criteria to select the number of classes. The latent class models were estimated in R 4.0.5 using the package "gmnl" developed by (Sarrias and Daziano 2017).

Results

Appendix E presents the sociodemographic characteristics of the two survey versions, dried cranberries, and cranberry juice, across four information treatment groups. Almost all groups of respondents were comparable to the general U.S. population regarding gender and income (U.S. Census Bureau 2020). The proportion of respondents with at least a four-year college degree in our sample was higher than the U.S. population, which is

[5]These variables were selected by running three ordinary least square regressions having the WTP for gene editing, regular sugar, and flavor as dependent variables and all responses to questions asked in the survey. The variables selected were the ones that were consistently statistically significant for all three regressions. Specific variables included: a binary variable equaling 1 if the income was higher or equal the sample average at $87.500/year; binary variable equaling 1 if the respondent indicated that the added sugar information on the NFP was important or crucial; binary variable equaling 1 if the respondent interpreted correctly the total sugar and the added sugar information on the NFP; binary variable equaling 1 if the respondent attributed their highest attention to the total sugar content on the NFP on a heat map question; binary variable equaling 1 if the respondent indicated that they liked extremely an intense cranberry flavor; binary variable equaling 1 if the respondent indicated that health was important/crucial when buying cranberry products; binary variable equaling 1 if the ingredient list was important/crucial when buying cranberry products; binary variable equaling 1 if they consider that CRISPR and GMO are different and they know the difference; binary variable equaling 1 if they consider that CRISPR and GMO are different but they don't know the difference; binary variable equaling 1 if they consider there are no differences between CRISPR and GMO; binary variable equaling 1 if they are willing to purchase CRISPR food if the breeding method information is the only information known; binary variable equaling 1 if they are willing to purchase CRISPR food if this increases insect resistance and herbicide tolerance; binary variable equaling 1 if they are willing to purchase CRISPR food if this reduces the environmental impact of food production, binary variable equaling 1 if they are willing to purchase CRISPR food if this increases nutrient content in food, binary variable equaling 1 if they are willing to purchase CRISPR food if this reduces the need to add sugars in food processing.

consistent with the profile of those who are more responsive to surveys in general (Curtin, Presser and Singer 2000). Moreover, compared to the general U.S. population, our sample contained a higher proportion of respondents with at least one child.

To ensure the sample of respondents across different information treatments was comparable, we used a pairwise t-test to examine statistical differences in salient sociodemographic characteristics across the treatment groups. We found that respondents in the two survey versions and across treatments were reasonably similar regarding gender, age, education, and income (Appendix E). Differences were observed in the cranberry juice survey sample, where the treatment four subsamples exhibited a higher proportion of respondents with larger family sizes (≥3 members) and at least one child in their households compared to the group responding to treatments 1–3 (Appendix E).

Willingness-to-pay results

All WTP models reported were estimated with unscaled random alternative-specific constants (ASCs), correlated parameters, and choice certainty on the scale parameter.

Dried cranberries

Across all treatments, respondents stated their willingness to discount the price of dried cranberries with regular compared to reduced sugar content (Table 3, Figure 1). The price discount ranged from \$2.33 to \$3.85. The information on the health benefits of cranberries – treatment 2 – did not impact the WTP (fail to reject the null hypothesis). Conversely, the price discount for regular sugar increased under treatment 3 – information on the recommendation to limit sugar consumption – and 4 – health benefits and dietary effects of reducing sugar intake (reject both null hypotheses). This coincides in part with (McFadden et al. 2021), who concluded that the information with negative connotations is more impactful than positive ones.

Respondents also consistently stated a discount for CRISPR compared to conventional-bred cranberries, ranging from \$1.43 to \$2.12 across information treatments. This finding is consistent with previous literature in which consumers favor conventional breeding over gene editing (An, Lloyd-Smith and Adamowicz 2019; Marette, Disdier and Beghin 2021; Muringai, Fan and Goddard 2020; Shew et al. 2018; Yang and Hobbs 2020). These results differ from Hu, House and Gao (2022), who found that respondents stated similar WTP for juice from gene-edited and conventionally bred oranges in the absence of information. Also, there were no statistically significant differences between the discount for CRISPR under the control and the different information treatments. This finding differs from studies concluding that information affected the WTP for CRISPR-bred foods (Paudel et al. 2023; Kilders and Caputo 2021; Hu, House and Gao 2022).

Importantly, the magnitude of the discount for regular sugar was more significant than the magnitude of the discount for CRISPR. This was further emphasized in the marginal rate of substitution (Appendix C) since we observed that the aversion toward products with regular sugar content was larger than that toward foods bred using CRISPR. This result is promising for the scientific community employing this new breeding technology in agriculture, as it implies that the aversion toward this new breeding method could be mitigated by offering consumers a product with reduced sugars.

Considering the magnitude of the WTP estimates, respondents placed flavor intensity as more important than the total sugar content when no information was provided and when both sets of information (health benefits and dietary effects of reducing sugar intake) were provided. This coincides with literature stating that consumers usually prioritize taste

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Table 3. Coefficient estimates for the dried cranberry model, considering information effects using the GMNL-II model in WTP space

	Coefficient estimates				Pairwise comparison between information treatments (t-stat)[1]		
	Information treatments						
Variables	1	2	3	4	1–2	1–3	1–4
Mean willingness to pay ($/6–oz bag)							
Sugar content: Regular vs. reduced	−2.33***	−3.54***	−3.56***	−3.85***	1.17	2.24**	4.02***
	(0.38)	(0.54)	(0.45)	(0.66)			
Breeding method: CRISPR vs. conventional breeding	−1.43***	−1.88***	−1.40***	−2.12***	0.94	0.02	1.44
	(0.28)	(0.34)	(0.29)	(0.47)			
Cranberry flavor: Bland/weak vs. full/intense	−3.00***	−3.12***	−2.79***	−4.27***	−0.69	−0.80	1.53
	(0.46)	(0.51)	(0.40)	(0.75)			
Opt-out	−4.78***	−5.27***	−5.41***	−4.83***	—	—	—
	(0.28)	(0.32)	(0.30)	(0.29)			
Standard deviation							
Sugar content: Regular vs. reduced	4.61***	5.54***	4.38***	5.87***	—	—	—
	(0.61)	(0.80)	(0.58)	(0.95)			
Breeding method: CRISPR vs. conventional breeding	2.73***	2.23***	2.62***	3.62***	—	—	—
	(0.45)	(0.61)	(0.49)	(0.79)			
Cranberry flavor: Bland/weak vs. full/intense	3.97***	3.18***	3.20***	3.97***	—	—	—
	(0.59)	(0.59)	(0.51)	(0.82)			
Opt-out	1.04***	0.17	1.29***	2.01***	—	—	—
	(0.34)	(0.76)	(0.33)	(0.35)			
Scale heterogeneity (τ)	−0.99***	1.29***	−0.92***	−0.94***	—	—	—
	(0.10)	(0.11)	(0.33)	(0.10)			
Certain	−0.44***	−0.40***	−0.51***	−0.79***	—	—	—
	(0.09)	(0.08)	(0.07)	(0.12)			
N. of observations	1500	1500	1500	1500			
Log likelihood	−1262.68	−1212.37	−1217.48	−1204.58			
Akaike information criterion	2557.35	2456.74	2466.95	2441.16			
Bayesian information criterion	2642.37	2541.75	2551.96	2526.17			

[1]The t-tests were based on the following hypotheses: H_{01}: $WTP^{treatment1}$ $WTP^{treatment2}$; H_{02}: $WTP^{treatment1} \leq WTP^{treatment3}$; H_{03}: $WTP^{treatment1} = WTP^{treatment4}$. The t-test uses WTP values that were bootstrapped from the normal distribution based on estimates from the GMNL-II model.
Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels.
Standard errors are in parentheses.

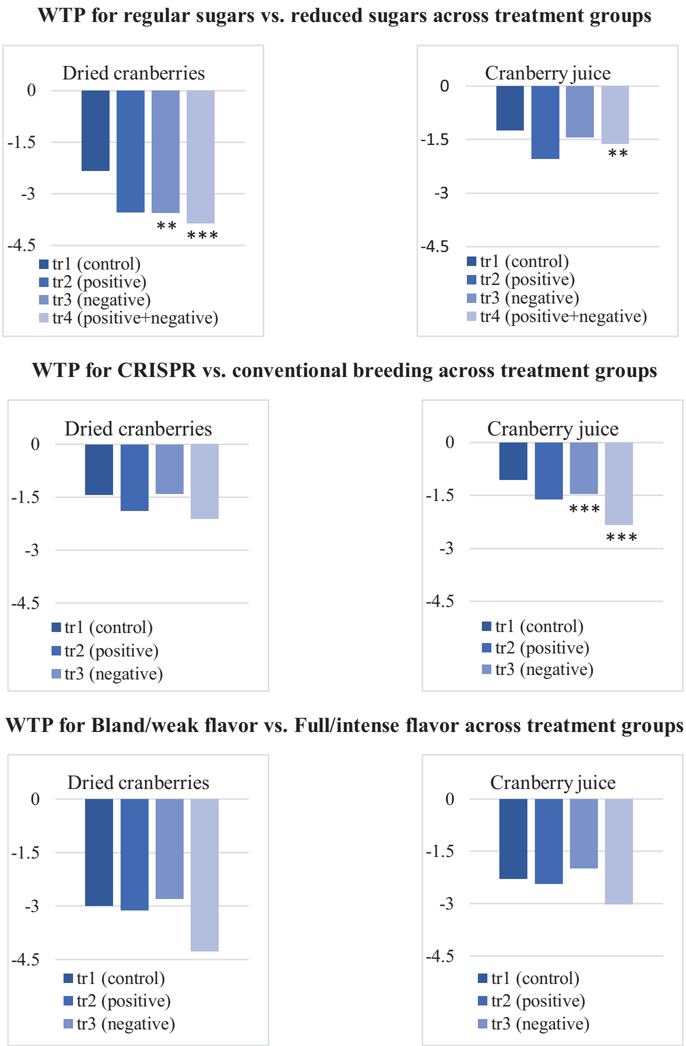

Figure 1. WTP across different information treatment groups of respondents. Notes: Single, double, and triple asterisks (*, **, ***) indicate the statistical significance of the pairwise t-tests at the 10%, 5%, and 1% levels. The pairwise t-tests were based on the following hypotheses: H_{01}: $WTP^{treatment1}$ $WTP^{treatment2}$; H_{02}: $WTP^{treatment1} \leq WTP^{treatment3}$; H_{03}: $WTP^{treatment1} = WTP^{treatment4}$. The t-test uses WTP values that were bootstrapped from the normal distribution based on estimates from the GMNL-II model.

over health when purchasing foods (Malone and Lusk 2017). In addition, our results indicate that when consumers see sugar-related health information, they are willing to trade-off a weaker flavor for lower sugar content. However, if no information about the need to limit sugar consumption is presented or when information that may counteract the health-related sugar message is presented (e.g., benefits from consuming cranberries), consumers are unwilling to trade-off a weaker flavor for reduced sugar content.

The opt-out ASCs were negative across all information treatments indicating respondents prefer the cranberry product alternatives over the no-buy option. The standard deviations of the random parameters and the standard deviation of the scale parameter, τ, were all statistically significant, indicating preference heterogeneity across respondents, and demonstrating the importance of considering variations in preferences. Also consistent with findings in Kilders and Caputo (2021) with more information – comparing treatment control with treatment 4 – the standard deviation of the mean WTP for reduced sugar and CRISPR increased, indicating that more information increased heterogeneity in responses. However, this is not consistent across the type of information. For example, comparing control with treatment 3 (effects of sugars on diet) the standard deviation of the WTP for reduced sugar and CRISPR decreases, indicating that this information leads to less heterogeneity in responses.

The parameter estimate for the certainty scale variable was statistically significant, although the results were inconsistent across information treatments. The negative sign associated with certainty meant that respondents who were certain about their choices made more stochastic choices. The literature offers no concluding findings on what should be the sign of this parameter. Beck, Rose and Hensher (2013) and Kunwar, Bohara and Thacher (2020) found that respondents who marked they were certain to make more deterministic choices. Conversely, Rahman and Bohara (2023) reported a positive sign for respondents were both certain and uncertain about their choices. These inconsistencies may be attributed to differences in the sample of respondents.

Cranberry juice

Similar to dried cranberries, respondents stated a price discount for regular sugar content ranging from \$1.23 to \$2.04 (Table 4, and Figure 1). Only, under treatment 4, when presenting both sets of information – cranberry health benefits and dietary effects of limiting sugar intake, the price discount significantly increased from \$1.23 to \$1.61 (reject the null hypothesis). Consistent with results from the dried cranberry survey, respondents stated a price discount for CRISPR that ranged from \$1.05 to \$2.33. Compared to the control treatment, the price discount for CRISPR was statistically larger when presenting information on the dietary effects of sugar intake (treatment 3) and both health benefits and dietary effects of sugar intake (treatment 4). We fail to reject the null hypothesis. This implies that accessing information increases expectations for cranberry products, increasing the aversion to the new CRISPR technology.

Consistent with findings from the dried cranberry survey, the cranberry juice survey respondents assigned higher importance to flavor intensity compared to regular sugar content and breeding method – across all treatments. Recall that flavor in this survey was described as the overall combination of sensations influenced by the taste, aroma, look, and texture. Because of the dilutions, the preference for an intense cranberry flavor is more evident for juices than dried cranberries. No clear pattern was observed in the effect of information on the discount for flavor intensity.

Similar to the dried cranberry survey models, the standard deviations of the parameters were statistically significant, denoting heterogeneity across respondents. The standard deviation of the scale parameter, τ, was statistically significant, and the parameter estimate for the certainty scale variable was negative and statistically significant. Here, with some exceptions, the additional information also increases the magnitude of the standard deviation of the WTP for reduced sugar content and CRISPR, leading us to conclude that more information increased heterogeneity in the WTP for these two attributes. This result coincides with (Kilders and Caputo 2021).

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Table 4. Coefficient estimates for the cranberry juice model, considering information effects using the GMNL-II model in WTP space

Variables	Coefficient estimates: Information treatments 1	2	3	4	Pairwise t-test comparison between information treatments (t-stat)[1] H01[1]: 1–2	H02: 1–3	H03: 1–4
Mean willingness to pay ($/64–fl. oz bottle)							
Sugar content: Regular vs. reduced	−1.23***	−2.04***	−1.44***	−1.61***	1.57	0.11	2.31**
	(0.19)	(0.29)	(0.21)	(0.28)			
Breeding method: CRISPR vs. conventional breeding	−1.05***	−1.61***	−1.46***	−2.33***	3.14	4.26***	7.04***
	(0.19)	(0.24)	(0.19)	(0.35)			
Cranberry flavor: Bland/weak vs. full/intense	−2.29***	−2.43***	−1.98***	−3.02***	−0.36	−2.04	0.90
	(0.29)	(0.30)	(0.23)	(0.41)			
100% juice	6.95***	8.78***	7.94***	8.15***	—	—	—
	(0.41)	(0.56)	(0.42)	(0.51)			
Cocktail	5.43***	6.92***	6.29***	6.67***			
	(0.38)	(0.50)	(0.37)	(0.47)			
Blend	5.45***	7.30***	6.31***	6.49***			
	(0.39)	(0.52)	(0.38)	(0.47)			
Standard deviation							
Sugar content: Regular vs. reduced	2.48***	3.23***	2.97***	3.32***	—	—	—
	(0.37)	(0.44)	(0.35)	(0.51)			
Breeding method: CRISPR vs. conventional breeding	0.75***	2.21***	1.79***	2.51***	—	—	—
	(0.26)	(0.33)	(0.26)	(0.40)			
Cranberry flavor: Bland/weak vs. full/intense	2.90***	2.71***	1.59***	2.63***	—	—	—
	(0.39)	(0.39)	(0.27)	(0.49)			
100% Juice	0.66***	2.59***	0.68**	0.85**	—	—	—
	(0.24)	(0.40)	(0.31)	(0.34)			
Cocktail	1.77***	2.40***	1.65***	0.26			
	(0.21)	(0.26)	(0.24)	(0.47)			
Blend	0.62	0.70***	1.17***	1.01***			
	(0.47)	(0.26)	(0.37)	(0.23)			
Scale heterogeneity (τ)	0.18	0.72***	0.65***	0.95***	—	—	—
	(0.12)	(0.08)	(0.06)	(0.10)			

(*Continued*)

Table 4. (*Continued*)

	Coefficient estimates				Pairwise t-test comparison between information treatments (t-stat)[1]		
	Information treatments						
Variables	1	2	3	4	H01[1]: 1–2	H02: 1–3	H03: 1–4
Certain	−0.34***	−0.29***	−0.11*	−0.47***	—	—	—
	(0.09)	(0.08)	(0.06)	(0.08)			
N. of observations	1500	1500	1500	1500			
Log likelihood	−1505.65	−1485.88	−1485.30	−1453.32			
Akaike information criterion	3069.31	3029.75	3028.60	2964.65			
Bayesian information criterion	3223.39	3183.83	3182.68	3118.73			

[1]The t-tests were based on the following hypotheses: H_{01}: $WTP^{treatment1}$ $WTP^{treatment2}$; H_{02}: $WTP^{treatment1} \leq WTP^{treatment3}$; H_{03}: $WTP^{treatment1} = WTP^{treatment4}$. The t-test uses WTP values that were bootstrapped from the normal distribution based on estimates from the GMNL-II model.
Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels.
Standard errors are in parentheses.

The opt-out ASCs for each juice label were positive and statistically significant, implying that respondents preferred each juice alternative over the no-buy option. In addition, the 100% juice was chosen over the cocktail and blend options.

Consistently, the standard deviations of the parameters were statistically significant, denoting heterogeneity across respondents, the standard deviation of the scale parameter, τ, was statistically significant, and the parameter estimate for the certainty scale variable was negative and statistically significant. Similar to dried cranberries, the additional information also increases the magnitude of the standard deviation of the WTP for reduced sugar content and CRISPR, leading us to conclude that more information increased heterogeneity in the WTP for these two attributes.

Compensating surplus results

We estimate the compensating surplus for products with different attribute levels and report those results in Figure 2. We find that respondents were willing to pay an overall price premium for a cranberry product made from CRISPR-bred cranberries, with reduced sugar content, and full/intense cranberry flavor relative to a product made with conventionally bred berries, regular sugar content and weak/bland flavor. Interestingly a higher premium was observed for dried cranberries ($3.90), compared to cranberry juice ($2.47). This implies that while the CRISPR attribute alone is disfavored by respondents, when it (CRISPR) is presented as part of a bundle of desired attributes such as reduced sugars and full/intense flavor, respondents were willing to pay a price premium for the desired bundle. In other words, respondents were willing to pay a premium for the desired bundle, as long as its price did not exceed the baseline prices of $3.90 for dried cranberries and $2.47 for cranberry juice. These insights suggest that when breeding methods such as CRISPR result in products with preferred product attributes, consumers may be willing to accept these products if the benefits offered offset consumer's discount for CRISPR.

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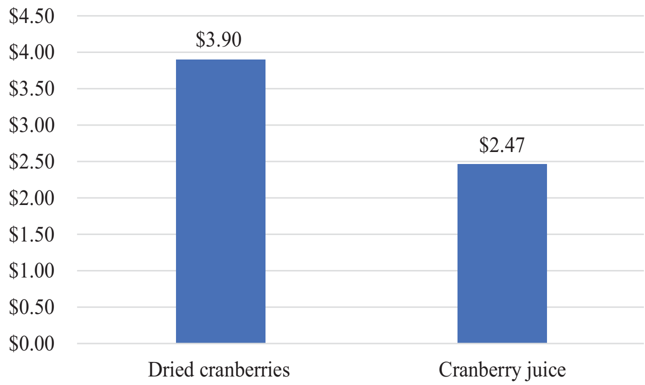

Figure 2. Compensating surplus for cranberry products to go from the base that is a cranberry product made with conventionally bred cranberries, with regular sugar content, and weak/bland flavor compared to the hypothetical case that is a cranberry product made with CRISPR-bred cranberries, with reduced sugar content, and full/intense flavor.

Latent class model results

To avoid confounding with information treatment effects, we only used the observations from the control treatment (no additional information) group in the latent class analyses. The three latent classes identified varied in the acceptance/rejection of the different attributes of dried and cranberry juice (Figure 3 and Appendix F-G). Concerning the acceptance of CRISPR, we found that for dried cranberries, a group was willing to pay a price premium for CRISPR compared to conventional breeding. This group stated they would purchase CRIPSR food if this reduced the need to add sugars in food processing. Also, this group was the least to correctly interpret the difference between total and added sugars and paid the least attention to total sugar content on the NFP.

For cranberry juice, one observes three segments of respondents: strong CRISPR rejection (class 1), mild CRISPR rejection (class 2), and the indifferent group (class 3). The indifferent group would display a larger proportion of respondents (compared to those who strongly reject CRISPR) with income ≥$87,500/year, larger proportion of respondents who know that CRISPR and GMO are different and they know the difference. The latter result is aligned with McFadden et al. (2021), in that there is some connection between the association of CRISPR to Genetic Modification and the acceptance of CRISPR. Interestingly, the group that shows a mild rejection to CRISPR had a larger proportion of respondents who indicated that they would be willing to purchase CRISPR food if this reduces the need to add sugars in food processing.

Conclusions and implications

Given the potential for abundant CRISPR applications to improve crops (and beyond), this study investigated respondents' WTP for this technology, considering that the benefit will be a product with reduced sugar content. Specifically, we examined respondents' WTP for regular sugar content (vs. reduced sugar content) and a product produced with cranberries developed using gene editing CRISPR (vs. conventional breeding). We examined cranberry products (dried cranberries and cranberry juice) because, despite their health benefits, cranberry products could be high in sugars – added by the industry to make them

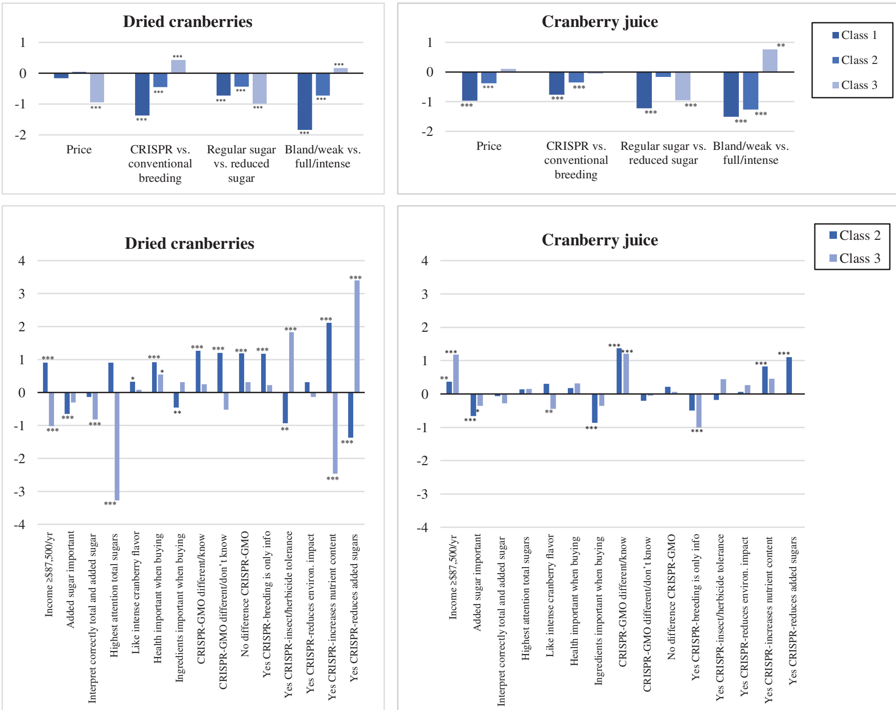

Figure 3. Latent class model results. Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance of the pairwise t-tests at the 10%, 5%, and 1% levels.

palatable. CRISPR could be used to develop cultivars with desired traits in terms of decreased acidity or increased natural sugar content). In general, across the three cranberry products evaluated, respondents stated willingness to discount the price for cranberries bred using CRISPR compared to conventional breeding, which is consistent with most literature (An, Lloyd-Smith and Adamowicz 2019; Marette, Disdier and Beghin 2021; Muringai, Fan and Goddard 2020; Shew et al. 2018; Yang and Hobbs 2020), with some exceptions (Hu, House and Gao 2022).

Participants were also willing to discount the price for cranberry products with regular sugar content compared to reduced sugar and for products with weak/bland flavor compared to full/intense flavor. The overall results were consistent even after presenting information scripts either emphasizing the health benefits of cranberries, the dietary effects of limiting sugar intake, or both. These findings differ from the literature, concluding that additional information impacts the WTP for CRISPR-bred foods (Hu, House and Gao 2022; Kilders and Caputo 2021; Paudel et al. 2023).

When analyzing the entire product, compensating surplus analyses indicate that consumers would be willing to pay a price premium for cranberry products that exhibit a reduced sugar content, are CRISPR-bred, and display a full/intense flavor relative to products with conventionally bred fruit but with less preferred attributes (i.e., regular sugar content and weak flavor). Respondents were heterogeneous in their preferences for CRISPR-bred cranberries. Consistently across the three cranberry products, those willing to pay a price premium for CRISPR-bred or those indifferent between CRISPR and conventional-bred cranberries stated they would purchase CRISPR food if this reduces the need to add sugars in food processing. This emphasizes the need to increase public awareness of the benefits of applying CRISPR to unaware population segments and those who believe that gene editing is another iteration of genetic modification.

Our results contribute to the scientific community interested in knowing how receptive consumers would be to new plant breeding technologies. The literature shows that consumers would be more acceptant if these technologies directly benefited them. This study shows that respondents were more reluctant to have a product with regular sugar content than a product using CRISPR-bred cranberries, as evidenced by the marginal rates of substitution between regular sugar content and CRISPR. Further, we show that respondents would be willing to pay a price premium for all three cranberry processed products if they exhibit a reduced sugar content, a full/intense cranberry flavor, and are CRISPR-bred. This study contributes to the food industry and policy makers' understanding of food choice drivers and could help inform the design of strategies and policies that will lessen consumers' pessimistic perceptions about novel breeding technologies, particularly when these technologies could lead to healthier food alternatives.

As a final point, a limitation of this study is the discrepancy in our goal to estimate WTP for reduced total sugars and the information treatment that mentions added sugars. We based the decision to mention added sugars in the information treatment, following the Dietary Guidelines for Americans (U.S. Department of Agriculture, Dietary Guidelines for Americans, 2020), that recommend limiting calories from added sugars and avoid foods and beverages with added sugars, but do not include recommendations for total sugars. Also, information on added sugars is more relevant considering the new FDA's labeling rule requiring products to explicitly report added sugars on the NFP in addition to the total sugar content. Moreover, literature suggests that consumers tend to focus on total sugar content more than added sugars (Tierney et al., 2017; Rampersaud et al., 2014). CRISPR offers the feasibility to develop cranberry varieties low in acid which would result in lower total sugar content reducing the need to add sugars. However, we acknowledge that based on how the information treatment was presented, we are unable to disentangle how respondents reacted to this information as we could be capturing mixed total sugar and added sugar avoidance reactions. Future research should consider assessing the dynamics of total sugar and added sugar labeling and the effect of health-related information on consumers' perceptions.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/age.2023.38.

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