The effect of the National Bioengineered Food Disclosure Standard (NBFDS) on consumer preferences and acceptance of bioengineered and gene-edited food

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Abstract: The National Bioengineered Food Disclosure Standard in the United States mandates disclosure of foods with bioengineered ingredients. However, some gene-edited foods are excluded from the Standard. This study explores consumer preferences and willingness to pay (WTP) for bioengineered and gene-edited foods, with a focus on romaine lettuce, in comparison to conventional, organic, and non-GMO alternatives. Our analysis includes three disclosure formats: the BE label, text, and QR code. We also determine the impact of information-seeking behavior on consumer valuations and the factors influencing such behaviors. Findings reveal a preference for conventional, organic, and non-GMO products over gene-edited and bioengineered options. However, the BE label is identified as the most favored disclosure method. In fact, under the BE disclosure, and particularly among information seekers, WTP for gene-edited and bioengineered products sometimes exceed WTP for conventional options. The study discusses policy implications regarding how disclosure formats and access to information can influence consumer perceptions and acceptance of new food technologies.

Key words: Gene-Editing, Bioengineering, National Bioengineered Food Disclosure Standard, Consumer Preferences, Consumer Demand.

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1. Introduction

The National Bioengineered Food Disclosure Standard (NBFDS) mandates a national standard for the disclosure of bioengineered foods and foods containing bioengineered ingredients. Since January 1 2022, food companies are required to disclose information on certain genetically modified (GM) food products using one of the following methods: (1) text ("bioengineered food" or "contains bioengineered food ingredients"), (2) a symbol (the Bioengineered (BE) label), (3) an electronic or digital link (QR code), and/or (4) a textual message on the package (USDA AMS 2021). This disclosure is to be applied to GM food products (defined as bioengineered food by the NBFDS), but not necessarily to gene-edited ones (Bloch, 2018; Molteni, 2019; National Sustainable Agriculture Coalition, 2019), as these decisions are made on a case-by-case basis (USDA AMS 2019; Jaffe 2019).

Professional associations such as the American Medical Association (2012) and the American Association for the Advancement of Science (2012) recommended against adopting the NBFDS to avoid unnecessary confusion among consumers (McFadden 2017). Research indeed indicates confusion, with consumers showing varying levels of understanding and awareness of gene-edited food, often failing to distinguish them from bioengineered food options (Caputo et al. 2022). Consumer advocacy groups are actively lobbying for the inclusion of gene-edited products in the NBFDS regulations, not just bioengineered ones, to foster transparency and informed food choices (Harmon, 2018). Studies demonstrate that consumer preferences for gene-edited over bioengineered foods often depend on the specific application and product (Hoban et al. 2019; Caputo et al. 2020; Chen et al. 2020), with a clear preference for gene-edited foods emerging when benefits are effectively communicated (Hallman et al. 2018; Caputo et al. 2020). Nonetheless, a research gap persists on consumer valuation of gene-edited versus bioengineered foods within the NBFDS disclosure framework.

We aim to target this gap by determining consumer preferences and willingness to pay (WTP) for gene-edited foods relative to bioengineered food options, considering various NBFDS approved information formats: label, text or QR code. To further increase the realism of our study, we also included products typically available in food markets against which consumers will make trade-offs. These are: conventional, USDA organic, and GMO-free. To achieve these objectives, we conducted an online survey of 2,004 U.S. consumers, centered around a hypothetical choice experiment on lettuce selection. Respondents were randomly allocated to eight distinct treatments, which varied in how the gene-edited and bioengineered options were disclosed to respondents: through a BE-label, a QR-code, or a combination of text, BE-label, and QR-code. In addition, within each group consumers were given the opportunity to access information about the different production methods: conventional, USDA organic, non-GMO, gene-editing, bioengineering. This experimental set up enabled us to evaluate the impact of the new NBFDS policy on consumer demand for both gene-edited and bioengineered foods compared to foods produced through alternative methods, while also evaluating potential variations in preferences for new food technologies between consumers who actively seek information and those who do not.

The results of this study offer several contributions to the existing food choice literature. One key contribution is the use of an experimental setting to investigate consumer preferences and WTP for both bioengineered and gene-edited food products under different information disclosures mandated by the NBFDS. Previous studies, such as McFadden and Lusk (2018) and McFadden et al. (2023), have examined consumer acceptance of and WTP for gene-edited food ingredients. However, McFadden and Lusk (2018) did not differentiate between bioengineered and gene-edited products, did not incorporate the BE-label as an information vehicle to indicate the presence of bioengineered ingredients, and did not permit respondents who opted for the QR code to access information about bioengineered ingredients. McFadden et al. (2023), on the other hand, focused on only two NBFDS disclosures, such as the BE label and text, and did not consider other products commonly available in grocery stores like USDA-Organic and non-GMOs. Our analysis bridges these gaps and provides fresh insights to policymakers, as well as marketers, farmers, and other stakeholders across the value chain who are interested in employing this technology and/or marketing their bioengineered and/or gene-edited products.

This study also provides valuable insights into the degree to which consumers seek out additional information about the food they purchase, and whether there are differences in product evaluations between consumers who seek out this additional information and those who do not. Our endogenous selection approach provides a novel angle relative to traditional approaches that randomly allocate people to different information treatments. This allows us to compare results from “information seekers” to those who do not seek additional information (non-information seekers). Information seekers might be particularly receptive to accepting gene-edited foods, as their proactive information-seeking behavior likely leads to greater knowledge and understanding, which can reduce misconceptions about new food technologies. Previous research has shown that consumer acceptance of GM foods can be influenced by the type of information consumers receive about those products (Lusk et al., 2004; Caputo, 2020), as well as the format through which messages are conveyed (Huffman, 2003; Huffman et al., 2003). Recent studies on consumer valuation for gene-edited foods have also confirmed this phenomenon (Shew et al., 2018; Yang and Hobbs, 2020; Kilders and Caputo, 2021). Our study contributes to this expanding body of knowledge by documenting how consumer preferences for novel biotechnologies are influenced by information seeking This insight holds importance to marketers seeking to determine the most effective strategies for successfully introducing these products into the market, as well as policymakers seeking to better understand the priorities and concerns of diverse consumers.

Lastly, except for the two food industry reports by Caputo et al. (2020, 2022), prior studies on gene-edited food products only included a comparison of gene-edited products with GM and/or conventional products (Shew et al. 2018; Yunes et al. 2019; Muringai et al., 2019, Yang and Hobbs 2020). Our third contribution lies in the implementation of a simulated food market, which extends beyond gene-edited and bioengineered options to include a variety of product alternatives commonly found at purchase points, including conventional, USDA organic, and non-GMO lettuce. This multi-product design improves the external validity of our findings, providing more realistic insights for industry stakeholders into the market potential of gene-edited food options under the NBFDS. Simultaneously, it introduces researchers and practitioners to an alternative experimental framework that facilitates a comprehensive evaluation of consumer demand for new food technologies.

2. Background and Research Hypotheses

The first GM foods used a form of genetic engineering (GE)[1] where the alteration of the genome typically involved the random insertion of a gene into the DNA of the target genome (Chen 2019). Despite this randomness, GM has resulted in crops that offer a variety of benefits. For example, within the agricultural sector, Dias and Ortiz (2013) point out the potential of GM vegetables to

[1] The umbrella term "genetic engineering" is defined as the "manipulation of an organism's genes by introducing, eliminating, or rearranging specific genes using the methods of modern molecular biology, particularly those techniques referred to as recombinant DNA techniques" (USDA, n.d.).

alleviate malnutrition around the world by offering better nutritional quality than conventional vegetables. Despite the potential benefits of GM technologies, public acceptance of the process has been lacking, in part, due to the concerns expressed about the unpredictability of the genetic modification process (Cardi 2016). This is particularly reflected in numerous studies that have found consumers generally prefer conventional foods over GM foods, with substantial discounts in willingness to pay for the latter (see e.g., Onyango and Nayga 2004; Lusk et al. 2005; Costa-Font et al. 2008; Lusk 2011), particularly in European countries (Lusk et al., 2003).

Scientists have developed new forms of GE breeding techniques, such as gene-editing. Gene-editing uses sequence-specific nucleases such as zincfinger nucleases (ZFNs) transcription activator-like effector nucleases (TALENs), and clustered regularly interspaced short palindromic repeats (CRISPR)-associated systems (CRISPR-Cas) to create targeted breaks in the DNA double-strand and then alter a specific DNA sequence (Huang et al. 2016). These alterations are specific and occur at controlled locations in comparison to the more random alterations and insertions of genetic material common in GM (Huang et al. 2016)[2]. As a result, gene-editing techniques have a substantially lower cost and a shorter development time than the first-generation of GE processes and have the potential to substantially advance plant and animal breeding. For example, gene-editing can produce nutritionally enriched tomatoes (Liao et al. 2017), breed disease-resistant pigs (Burkard et al. 2017) and generate genetically hornless dairy cows (Carlson et al. 2016; Kilders and Caputo 2021), among other benefits.

Early studies on consumer acceptance of gene-edited food products focused on comparisons with conventional or GM alternatives, where GM alternatives were denoted with the term "Genetically Modified" instead of bioengineered. Results from these studies draw contradictory conclusions. An et al. (2019) compared Canadian consumer preferences and WTP for gene-edited and GM canola oil[3]. They find that respondents are willing to pay a premium of 27%-47% over average canola oil prices in Canada for the gene-edited alternative compared to the conventional canola oil. Muringai et al. (2020) documented that Canadian consumer had a higher

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[2] See Araki and Ishii (2015) and Ishii and Araki (2016) for a discussion of the different breeding techniques, their pros and cons, as well as policy recommendations for the integration of gene-edited crops into society.

[3] Since virtually all the canola grown in Canada is of the GM variety, they label the "conventional" alternative as "Conventional (GM) canola oil", despite a lack of regulations for labeling GM food products in Canada (Government of Canada, 2020).

discount for GM potatoes relative to gene-edited potatoes, with both experiencing a discount relative to conventional ones. Shew et al. (2018), found that both GM and gene-edited rice alternatives were discounted similarly compared to the conventional rice by Canadian, US, Australian, Belgium, and French consumers. Drawing from the results of these previous studies, we formulated our study's first hypothesis: we hypothesize that consumers will have a lower WTP for gene-edited and bioengineered foods relative to other non-GE alternatives irrespective of the gene-editing and bioengineering disclosure method or whether they access additional provided information or not (**H_{01}**).

More recent studies have compared consumer preferences for meat and plant-based gene-edited foods both in a fresh and processed stage over GM products termed "bioengineered" as well as conventional, organic, and non-GMO foods (Caputo et al, 2020). However, the study only used the BE-label conceptualized under the NBFDS to symbolize the bioengineered alternative and text to denote the gene-edited product. Alternative disclosure options were not tested. This limited assessment of disclosure options is relevant as McFadden and Lusk (2018) demonstrate that consumer's WTP for GM apples and granola bars with genetically engineered ingredients differed depending on whether the bioengineered status was disclosed via text or QR-code. The use of the latter has significantly increased in the last years, with a 94% growth in the number of QR interactions between 2018 and 2020 (Bluebite 2021). Indeed, McFadden and Lusk (2018) found that a text disclosure lowered WTP relative to a QR disclosure that required respondents to scan the code. However, as mentioned in the introduction section, the authors' comparison did not incorporate the new BE-label, which represents an alternative way of indicating the presence of bioengineered ingredients and did not ask respondents to choose between multiple available product alternatives as commonly found in a grocery store, but rather asked respondents to choose between only two available options[4]. Building upon the findings of this second stream of literature, we expect to find differences in consumer's evaluation of gene-edited and bioengineered alternatives depending on whether their GE status is disclosed via a text, a label, a QR-code, or a combination thereof (**H_{02}**).

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[4]The two options reported different labels in varying combinations (i.e., QR-Code indicating that the product contained genetically engineered ingredients when scanned, the non-GMO project verified label, USDA organic label, and a text stating "contains genetically engineered ingredients").

Research into consumer acceptance of gene-edited and GM foods has also revealed substantial variation in consumer preferences. These findings align with earlier results from meta-analysis studies indicating that consumers acceptance of and WTP for GM products vary across products, geographical contexts, the experimental context, respondent knowledge, and whether information was provided to respondents or not (see e.g., the meta-analyses by Lusk et al. 2005, 2011). The impact of information provision has been of particular interest. More recent studies indicate that providing respondents with both neutral (Hu et al. 2022) and benefit (Caputo et al. 2020) information of gene-editing and genetic modification positively impacts WTP. However, in contrast to how information is taken in, in real life, most of the existing studies forced respondents to be confronted with the information instead of giving them the option to seek it out or avoid it. Thus, results of the actual impact of information might be biased due to the inclusion of respondents who would have otherwise avoided being confronted with additional facts. In light of this, we postulate that differences in WTP for the GE foods are not only driven by disparities in the disclosure method, but likewise stem from differences in consumer's decision to access additional information on the production methods or not ($\mathbf{H_{03}}$).

Building on our third hypothesis, we also posit that the decision to access information on the production methods is at least partially associated with attitudinal and socio-demographic factors ($\mathbf{H_{04}}$). Kim et al. (2023) recently found that the sample composition in terms of consumption habits, socio-demographics and other factors differed between information seekers and non-seekers, with these differences being statistically correlated with variations in WTP for plant-based seafood alternatives.

Collectively, by testing these four hypotheses, this study adds to this existing literature by evaluating the effect of different NBFDS disclosure options on consumer preferences for both gene-edited and bioengineered products relative to conventional, organic, and non-GMO alternatives.

3. Materials and Methods

3.1 Experimental Design

To test our hypotheses and answer our underlying research questions, we used an online survey centered around a discrete choice experiment (DCE) to elicit consumer food preferences for romaine lettuce selection. The DCE method is widely used in the food choice literature (see Caputo and Scarpa 2022 for a review) and has shown high external validity for products not yet available in food markets (Brooks and Lusk 2010). We selected this method for two reasons. First, at the time of data collection, the only gene-edited food product commercially available in the US market was a high oleic soybean oil, which had limited distribution and was mostly directed towards the food industry (Labant 2020). Second, since the NBFDS began in January 2022, the utilization of scanner data to elicit consumer preferences and demand for both bioengineered and gene-edited products was unfeasible at the time of the data collection.

Romaine lettuce was chosen as the product of interest due to its widespread consumption among US consumers and existing gene-editing applications[5]. In 2020 alone, the value of romaine lettuce production was nearly $950 million (USDA NASS 2021), with Americans consuming more than 25 pounds of lettuce per person annually (Agricultural Marketing Center 2021). To create a more realistic representation of the U.S. supermarket experience, we adopted a product-specific (labeled) experimental design that has been used in recent food DCE applications (Lusk and Tonsor 2016, Caputo et al. 2020, Van loo et al. 2020, Kilders and Caputo 2024). In this labeled design, participants were presented with five romaine lettuce options - conventional, USDA organic, non-GMO, bioengineered, and gene-edited - at different prices levels. We also included a "none" option to increase the realism of the choice task. This set-up also allows us to test **H1**, i.e., whether consumers indeed discount GE foods relative to alternative production methods.

To determine the appropriate price levels, we consulted pricing information from the U.S. Bureau of Labor Statistics, the USDA, and popular supermarkets and wholesalers throughout the United States. The price ranges we selected were $0.99, $1.99, $2.99, and $3.99 for the gene-edited, bioengineered, and conventional options, and $2.99, $3.99, $4.99, and $5.99 for the USDA organic and non-GMO lettuce. The price premium for the USDA organic and non-GMO products was incorporated into the experimental design to reflect the actual pricing in food markets. The

[5] There are at least two main gene-editing applications under development for romaine lettuce. The first application, developed by UC Davis, aims to create lettuce variants that are more resistant to heat (CropLife n.d.). This application primarily benefits farmers and the environment by reducing food loss during production. The second application, developed by the Intrexon Corporation, involves creating non-browning romaine lettuce (Paarlberg 2021).

price levels appearing in each choice question were determined by a main effects orthogonal fractional factorial design, which makes the prices of each choice alternative uncorrelated with the other alternatives. A perfectly orthogonal design required 12 choice questions, each including five product alternatives offered at different prices. To prevent respondent fatigue, we split these 12 choice questions into two blocks of 6 choice questions each. Therefore, respondents were presented with six choice questions during the survey, each featuring five romaine lettuce products and the "none" option. An example of a DCE question is provided in Figure 1.

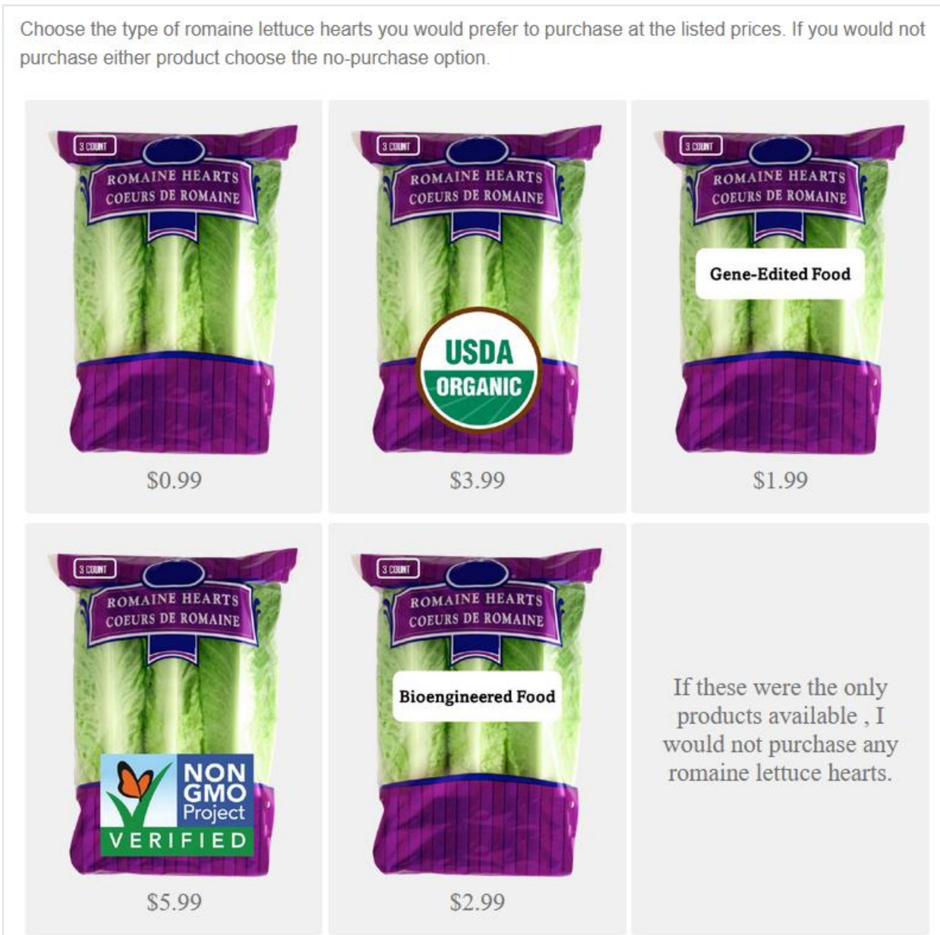


Figure 1. Example of a choice question.

3.2 Treatments

The DCE questions described above were used to elicit consumer preferences and demand for both bioengineered and gene-edited romaine lettuce under the NBFDS. To this end, we used a between-subject approach and employed different combinations of texts, labels and QR codes to reflect the options permitted under the NBFDS. This resulted in eight treatments, which are outlined in Table 1.

Table 1: Outline of the treatments

Treatments	Product under consideration	Disclosure	Explanation/Labelling
B: Text G: Text	Bioengineered Lettuce	Text	Bioengineered Food
	Gene-edited Lettuce	Text	Gene-Edited Food
B: Label G: Text	Bioengineered Lettuce	Label	
	Gene-edited Lettuce	Text	Gene-Edited Food
B: Text G: Label	Bioengineered Lettuce	Text	Bioengineered Food
	Gene-edited Lettuce	Label	
B: Combo G: Combo	Bioengineered Lettuce	Text + Label	Bioengineered Food –
	Gene-edited Lettuce	Text + Label	Gene-Edited Food –
B: Digital G: Text	Bioengineered Lettuce	Digital	
	Gene-edited Lettuce	Text	Gene-Edited Food
B: Digital G: Label	Bioengineered Lettuce	Digital	
	Gene-edited Lettuce	Label	
B: Text G: Digital	Bioengineered Lettuce	Text	Bioengineered Food
	Gene-edited Lettuce	Digital	
B: Label G: Digital	Bioengineered Lettuce	Label	
	Gene-edited Lettuce	Digital	

The treatments differed based on the type of NBFDS disclosure used to describe the bioengineered and gene-edited product alternatives in the DCE questions, thus allowing us to test

H2 (WTP for GE foods under different disclosure options). The first four treatments (B:Text-G:Text, B:Label-G:Text, B:Text-G:Label, B:Combo-G:Combo) compared text disclosure to symbol disclosure, where the bioengineered and gene-edited alternatives were described as either "Bioengineered Food/Gene-Edited Food" for the text disclosure or using the "BE label" (see Appendix A2) for the symbol disclosure. The latter four treatments (B:Digital-G:Text, B:Digital-G:Label, B:Text-G:Digital, B:Label-G:Digital) compared text or symbol disclosure to digital disclosure, where the bioengineered and gene-edited product alternatives were described using the "Bioengineered Food/Gene-Edited Food" for the text disclosure, the BE label for the symbol disclosure, and a QR code for the digital disclosure. The QR code used in the choice questions included the text "Bioengineered Food" or "Gene-Edited Food", depending on the treatment. For example, Figure 1 illustrates an example of a choice question where the gene-edited and the bioengineered alternatives are both marketed with the text NBFDS disclosure.

Within each treatment, respondents were also given the option to access additional product information related to the various production methods before proceeding to the DCE questions. Respondents who stated not to be interested in accessing additional product information were automatically directed to the DCE questions of one of the eight treatments. Respondents who stated to be interested in receiving additional information, were provided with information briefly describing the production methods of the various product alternatives before answering the choice questions, as outlined in Table S1 in the Appendix C. The product information was framed to reflect actual information available to consumers in various outlets. For example, the information used for bioengineered food reflects the definition provided by the USDA (see here). For the treatments incorporating the digital disclosure for either the gene-edited or bioengineered option, the information about gene-edited and bioengineered alternatives were delivered via QR-code. When scanning the QR-code on either the bioengineered or the gene-edited alternative, a website opened on the device used by the respondent to scan the code. The website showed the same respective production information for either the bioengineered (B:Digital-G:Text, B:Digital-G:Label) or the gene-edited option (B:Text-G:Digital, B:Label-G:Digital).

In this experimental setup, respondents were divided into two groups: information seekers (i.e., respondents who chose to access information) and non-information seekers (i.e., those who prefer to forego additional information). We used these two segments to test our third hypothesis, **H3,** as described in section 2. The survey also collected data on socio-demographic characteristics, attitudes toward new food technologies and knowledge of GE products. These additional variables were used to examine **H4**, which aims to identify the determinants of a respondent's information-seeking status. We postulate that consumers who are more educated and knowledgeable about GE technologies show a more pronounced information-seeking behavior. We also anticipate a more pronounced information-seeking behavior among consumers who believe decisions about the labeling of new food technologies should primarily be based on the views of the average American.

3.3 Econometric Analysis

The DCE data was analyzed using a mixed logit model (MXL). The MXL allows us to account for random taste variation (preference heterogeneity) and has the capacity to approximate any true underlying random utility model (McFadden and Train 2000; Train 2009). For each product of interest and information treatment, the utility that consumer n derives from product alternative j at choice situation t is expressed as follows:

$$U_{njt} = \sum_{j=1}^{5} \beta_{nj} - \alpha_n PRICE_{njt} + \varepsilon_{njt} \quad (1)$$

where j represents the alternatives, a respondent could choose between (conventional, organic, non-GMO, bioengineered, and gene-edited). For identification purposes the utility of the "none of these" option was normalized to zero. $PRICE_{njt}$ is a continuous variable populated with the four price levels in the design; α_n is the coefficient capturing the price effect; ε_{ij} is the *i.i.d.* type I extreme value distributed random error term. In this application, the coefficients of the alternative specific constants are assumed normally distributed in the population, while the price parameter is assumed to follow a one-sided triangular distribution. The parameters are estimated via a simulated maximum likelihood estimation based on 1000 Halton draws (see Train, 2009 for details).

The coefficients from the MXL models were used to calculate the total WTP for each product alternative j (conventional, organic, non-GMO, bioengineered, and gene-edited) versus the "none" option. The total WTP values were then translated into marginal WTP values. The total WTP refers to the dollar premium that would induce a consumer to be exactly indifferent to buying alternative j versus the "none"-baseline, whereas marginal WTP refers to the dollar premium that would induce a consumer to be exactly indifferent to buying alternative j (for example gene-edited lettuce) versus alternative k other than the "none" option (for example GMO lettuce). Marginal

WTP for product j versus product k was calculated by subtracting the total WTP for product j from the total WTP for product k. We used the Krinsky and Robb (1986) bootstrapping method to approximate the asymptotic sampling distribution of total and marginal WTPs from each treatment. The 1000 bootstrapped values were then used to explore distributional patterns of marginal WTP across the treatments via boxplots.

Previous studies indicate that different labeling programs and information affect market shares for emerging food products (Lusk 2018; Van Loo et al. 2020). Therefore, we also generated demand curves for the bioengineered and gene-edited product alternatives for a subset of treatments, in which consumers showed the highest evaluation for gene-editing and bioengineered options. In doing so, we implemented the same procedures originally used by Lusk and Tonsor (2016) and adopted in other recent food choice studies (Caputo et al. 2020; Van Loo et al. 2020). Finally, in the last step of our analysis, we estimated various logit models to examine factors affecting information-seeking behaviors, specifically factors influencing consumers to read more information about the products or scan the QR code to access more information about the gene-edited or bioengineered options.

4. Data

The DCE was implemented using a nationwide online survey. The survey was designed in Qualtrics, and data collection was conducted by Dynata in November 2021. We obtained 2,004 completed responses in total, which were randomly distributed over eight treatments. Table 1 presents the demographics of the overall sample; as well as the demographics of the two endogenously determined information groups: information seekers and non-information seekers. The characteristics for the individual treatments are also reported in Appendix, Table A1. There were no significant differences across treatments in terms of socio-demographics.

Overall, the full sample closely resembled the U.S. population; however, some expected differences were observed with regard to gender, age, and education. The higher proportion of females in the sample (~56%) is appropriate, considering our criteria that the majority of grocery shopping must have been done by the respondent. The higher age of the sample is likely due to our requirement that respondents be at least 18 years old. Also, a higher percentage of our sample had completed college-level education compared to the U.S. Census. This finding is consistent with other food-related studies and reflects the higher likelihood of better-educated individuals participating in online surveys (Singer et al., 2000). Notably, 59% of respondents chose to access the information, while the remainder expressed disinterest. Furthermore, among those assigned to one of the treatments involving QR codes, 23% scanned the code.

In the following sections, we will first examine how consumer preferences and willingness to pay for bioengineered and gene-edited lettuce vary among different disclosure options, distinguishing between information seekers and non-seekers. We will then explore the factors that influence consumers' decisions to seek additional information about the products and to scan the QR codes.

Table 1. Socio-demographic Characteristics of the Sample

Variable	**Description**	**Full Sample**	**Information Seeker**	**Non-Information Seeker**
Female	1 if respondent is female, 0 otherwise	0.56	0.54	0.60
Age	Mean age in years	47	45	51
College	1 if respondent completed at least a 4-year degree, 0 otherwise	0.39	0.42	0.35
Adults	Mean number of adults in household	2	2.01	1.97
Children	Mean number of children in household	1.64	1.73	1.50
Low Income	1 if household income is below 75,000, 0 otherwise	0.71	0.69	0.73
QR-Code[a]	1 if respondent scanned the QR-Code, 0 otherwise	0.23	0.33	0.07
Number of respondents		2003	1189	814

[a]The average for the full sample only aggregates T5-T8 as no QR code was present to scan in T1-T4.

5. Results

5.1 Consumer preferences and wiliness to pay estimates and information seeking behavior.

We conducted two likelihood ratio (LL) tests. The first LL test was conducted to test the null-hypothesis of coefficients equality between the non-information seekers and information-seekers groups within each disclosure treatment. Once again, the null hypothesis was rejected at the $p < 0.01$ level (chi-square value of 171.32), suggesting that information seeking behavior influences the parameter estimates. The second LL test was conducted within each information group, to test the null hypothesis that coefficients are equal across the eight treatments. The null hypothesis is rejected at the $p < 0.01$ level (chi-square values of 181.95 and 278.37 for information seekers and non-information seekers respectively) in both treatments, indicating the significant impact of the diverse NBFDS disclosures on parameter estimates. Accordingly, and in alignment with our main research hypotheses, we present the results disaggregated by information-seeking behavior (seekers and non-seekers), and treatments.

We start by examining the total and marginal WTP[6] for the various lettuce types (conventional, organic, non-GMO, bioengineered, and gene-edited lettuce) within the eight treatment estimates for the non-information seekers. The findings are presented in Table 3 (the underlying estimates of the MXL segmented models are in Appendix, Table A1), with corresponding standard errors indicated in parentheses and confidence intervals in brackets[7]. We remind the reader that in in the first four treatments (B:Text-G:Text, B:Label-G:Text, B:Text-G:Label, Combo-Combo), we tested a combination of text and label disclosures, whereas in the latter four treatments (B:Digital-G:Text, B:Digital-G:Label, B:Text-G:Digital, B:Label-G:Digital), we examined a combination of text, label, and QR code disclosures. The QR code included in the choice questions represented either the gene-edited lettuce or the bioengineered lettuce. The non-information seekers who scanned the QR code during the choice experiment represent on average 5% of the sample across treatments, 5~8.

[6]We remind the reader that total WTP values indicate how much consumers are willing to pay for each product compared to the "none" (or no-buy) option.

[7]The standard errors and confidence intervals were computed using the Krinsky and Robb (1986) bootstrapping method.

Table 3. Total WTP estimates of segmented by Treatments based on the Mixed Logit Models, non-information seekers

… vs. None	**B:Text-G:Text**	**B:Label-G:Text**	**B:Text-G:Label**	**Combo-Combo**	**B:Digital-G:Text**	**B:Digital-G:Label**	**B:Text-G:Digital**	**B:Label-G:Digital**
Conventional	3.45* (0.29) [2.87,4.02]	4.2* (0.34) [3.53,4.87]	4.2* (0.35) [3.51,4.88]	4.89* (0.42) [4.08,5.7]	3.84* (0.3) [3.26,4.42]	3.6* (0.29) [3.03,4.18]	3.99* (0.32) [3.37,4.61]	3.85* (0.34) [3.19,4.52]
non-GMO	4.68* (0.26) [4.18,5.18]	4.65* (0.34) [3.99,5.31]	4.57* (0.43) [3.72,5.41]	5.32* (0.47) [4.41,6.24]	3.39* (0.57) [2.28,4.49]	3.79* (0.41) [2.99,4.58]	4.6* (0.33) [3.95,5.26]	4.7* (0.38) [3.95,5.44]
Organic	4.52* (0.27) [3.98,5.05]	4.99* (0.31) [4.38,5.6]	5.07* (0.39) [4.3,5.84]	6.08* (0.43) [5.23,6.92]	4.26* (0.4) [3.48,5.03]	4.3* (0.3) [3.71,4.89]	4.74* (0.34) [4.07,5.41]	4.68* (0.45) [3.8,5.56]
Bioengineered	-0.28 (0.79) [-1.83,1.27]	1.72* (0.52) [0.7,2.75]	2.02* (0.37) [1.29,2.74]	2.42* (0.49) [1.47,3.37]	3.26* (0.27) [2.72,3.8]	3.01* (0.25) [2.51,3.51]	0.63 (0.66) [-0.67,1.93]	2.35* (0.35) [1.67,3.04]
Gene-Edited	-0.28 (0.79) [-1.83,1.27]	0.23 (0.77) [-1.28,1.74]	3.47* (0.37) [2.74,4.2]	1.66* (0.7) [0.3,3.03]	2.01* (0.38) [1.26,2.76]	3.09* (0.3) [2.49,3.68]	3.40* (0.34) [2.73,4.06]	2.92* (0.35) [2.23,3.61]
N. of respondents	97	102	102	106	111	98	88	110

Note: * indicate significance at the 5% level. Standard errors are presented in round brackets and confidence intervals are presented in square brackets.

Our results show a clear preference hierarchy among respondents, regardless of the treatment. Consumers are willing to pay the highest premium for USDA organic lettuce relative to the "none" option (\$6.08~\$4.26), followed by non-GMO (\$5.32~\$3.39) and conventional (\$4.89~\$3.45) lettuce. The lowest WTP values are associated with both the bioengineered and gene-edited options, with WTP values ranging from \$-0.28 to -\$3.31 for bioengineered lettuce and from \$-0.28 to - \$3.47 for gene-edited lettuce. This result corroborates **H1** and provides evidence of low consumer acceptance of both GE products compared to USDA organic, non-GMO and conventional options.

Our findings for the information seekers, which are reported in **Table 4**[8], further corroborate a rejection of the null hypothesis for **H1**. The information seekers represent consumers who chose to access the additional product information available to them before the DCE exercise[9], which represents 59% of our sample. Again, we find that the average total WTP is highest for the USDA organic lettuce followed by the non-GMO and conventional alternative. The results also indicate that the total WTP for gene-edited lettuce varies across disclosure treatments. Consistent with the non-seekers, the highest total WTP values for the gene-edited option are found in treatments where the alternative carries the BE label, with the highest total WTP of \$3.47 in the B:Text-G:Label treatment. On the other hand, treatments where the disclosure is done via a text for the gene-edited option, as for example the B:Text-G:Text treatment and the B:Label-G:Text treatment, show comparatively low WTP values for the gene-edited lettuce. This evidence supports **H2**, meaning there are indeed differences in the WTP across disclosure methods.

[8] The standard errors (in parenthesis) and confidence intervals (in brackets) are constructed using the Krinsky and Robb (1986) bootstrapping method, while the underlying estimates of the MXL segmented models are in the Appendix, Table A2.

[9] Please note that in treatment 5-8 respondents who had opted into seeing the information (i.e., information seekers) also had to scan the QR-code to see information about the alternative it was applied to in the respective treatment (either the gene-edited or bioengineered lettuce). Across treatments only about 23% of respondents did so. Due to the small percentage of respondents doing this, the data were analyzed merging both groups, and implications of this strategy are discussed in the text and conclusion section.

Table 4. Total WTP estimates segmented by Treatments based on the Mixed Logit Models, information seekers

….vs. None	B:Text-G:Text	B:Label-G:Text	B:Text-G:Label	Combo-Combo	B:Digital-G:Text	B:Digital-G:Label	B:Text-G:Digital	B:Label-G:Digital
Conventional	4.87* (0.57) [3.75,6]	3.39* (0.34) [2.72,4.05]	4.69* (0.38) [3.94,5.44]	4.39* (0.37) [3.67,5.12]	3.71* (0.38) [2.97,4.44]	4.18* (0.45) [3.29,5.07]	5.74* (0.43) [4.9,6.59]	4.12* (0.36) [3.42,4.82]
non-GMO	6.58* (0.5) [5.59,7.56]	4.53* (0.37) [3.8,5.27]	5.89* (0.47) [4.97,6.82]	4.97* (0.42) [4.14,5.8]	4.97* (0.41) [4.16,5.78]	5.28* (0.45) [4.4,6.15]	6.4* (0.47) [5.48,7.32]	5.26* (0.43) [4.42,6.1]
Organic	6.87* (0.48) [5.92,7.82]	5.24* (0.39) [4.47,6]	6.43* (0.42) [5.62,7.25]	5.94* (0.38) [5.2,6.68]	5.79* (0.36) [5.1,6.49]	6.41* (0.48) [5.46,7.36]	6.75* (0.45) [5.86,7.63]	5.82* (0.43) [4.98,6.65]
Bioengineered	2.66* (0.55) [1.58,3.73]	2.41* (0.38) [1.67,3.15]	2.44* (0.53) [1.41,3.48]	2.67* (0.39) [1.9,3.45]	2.86* (0.34) [2.19,3.54]	3.30* (0.47) [2.38,4.23]	3.53* (0.44) [2.67,4.39]	3.91* (0.41) [3.11,4.72]
Gene-Edited	3.19* (0.6) [2.02,4.36]	2.03* (0.43) [1.19,2.87]	4.22* (0.41) [3.43,5.02]	2.77* (0.48) [1.83,3.7]	2.18* (0.48) [1.24,3.11]	4.51* (0.41) [3.72,5.31]	5.47* (0.41) [4.66,6.27]	4.41* (0.37) [3.69,5.13]
Number of Respondents	161	146	139	140	136	168	152	147

Note: * indicate significance at the 5% level. Standard errors are presented in round brackets and confidence intervals are presented in square brackets

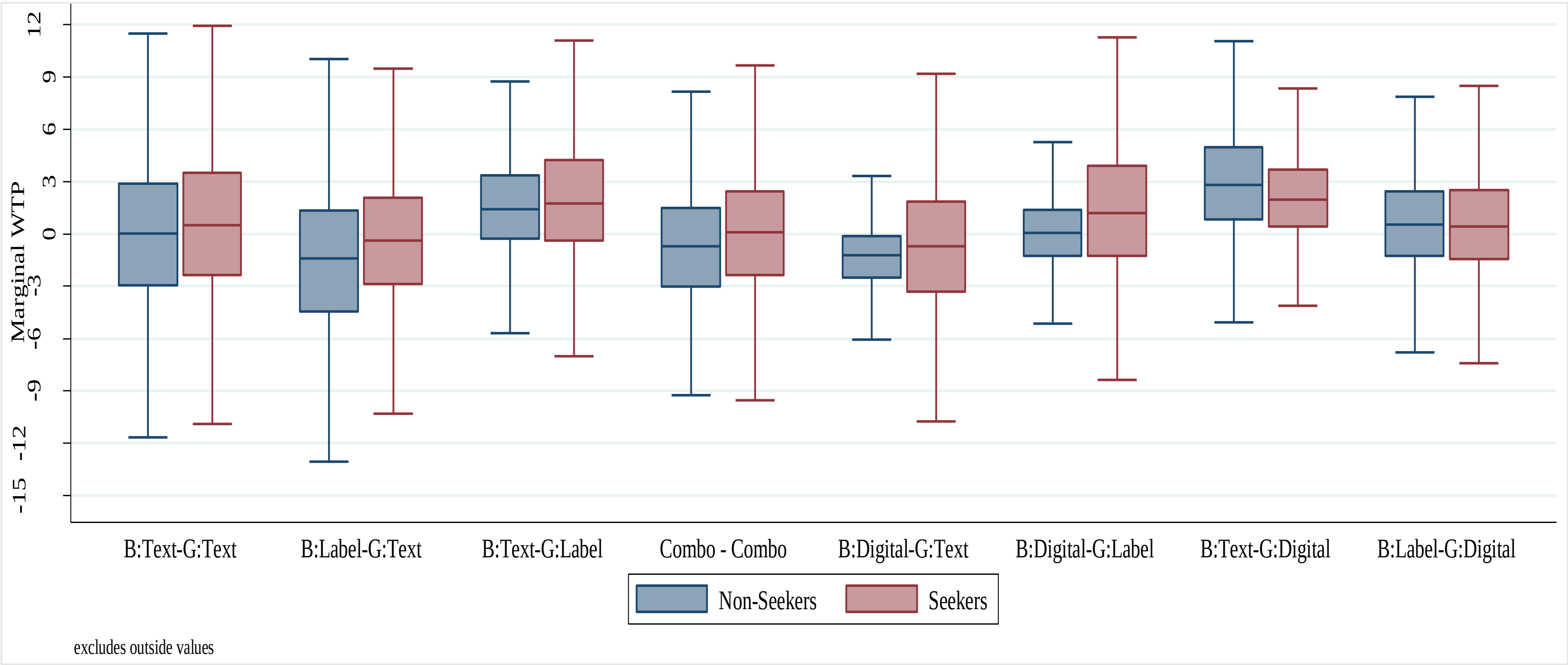
The impact of different NBFDS disclosure formats is even more pronounced when looking at the marginal WTPs for the gene-edited alternative versus the bioengineered one across treatments and information-seeking groups (non-information and information seekers). Thus, Figure 2 displays the treatment and information-seeking group respective boxplots for the marginal WTP of the gene-edited versus bioengineered romaine lettuce[10]. The boxplots were generated via bootstrapping following the procedures outlined in Krinsky and Robb (1986).

In line with **H2**, we find substantial differences in the marginal WTP across disclosure mechanisms. For example, looking at the non-information seekers, we note a positive and significant marginal WTP of $1.78 for the gene-edited alternative relative to the bioengineered in the B:Text-G:Label treatment emphasizing respondent's general preference for the label over the text. Respondent's dislike for the text disclosure is further emphasized when looking at the non-information seekers in the B:Digital-G:Text treatment where we observe a negative marginal WTP value of -$0.68 for the gene-edited lettuce relative to the bioengineered one.

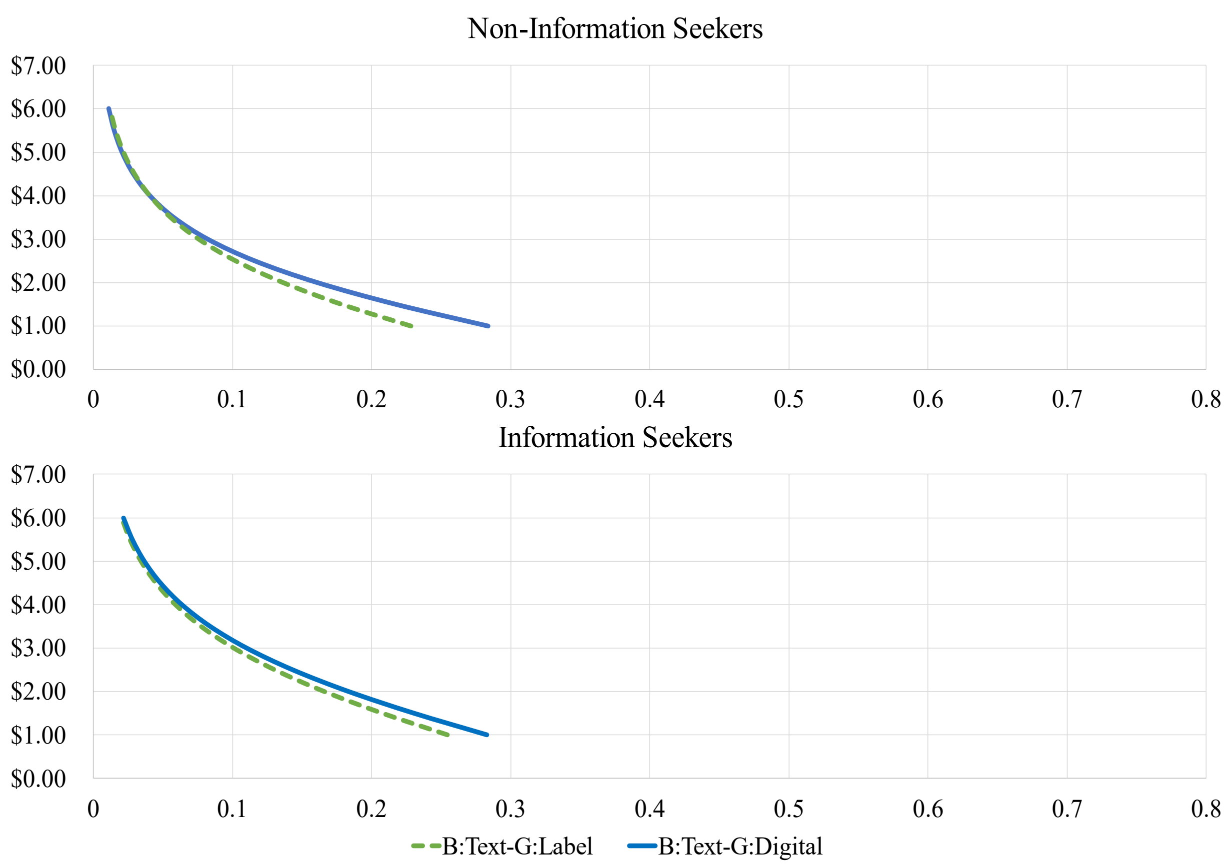
Furthermore, providing support for our third hypothesis (**H3**), we find significant differences in marginal WTP across non-information seekers (blue bars) and information seekers (red bars). Importantly, aside from the B:Label-G:Text and B:Text-G:Digital treatment, we observe a higher variability in marginal WTP among information-seekers than non-seekers. This result corresponds with results by Kilders and Caputo (2021) which highlight that information gathering is associated with a larger heterogeneity in preferences. It is also worth noting that in the B:Text-G:Digital treatment, the gene-edited option was described by the QR code. However, only 5% of consumers scanned it. This finding raises questions about the effectiveness of QR codes as a means to deliver information to consumers, especially in the context of disclosing whether a food is bioengineered, or gene-edited.

[10] The mean marginal WTP estimates for all products including the standard errors and confidence interval values can be found in the Appendix in Tables A3 and A5.

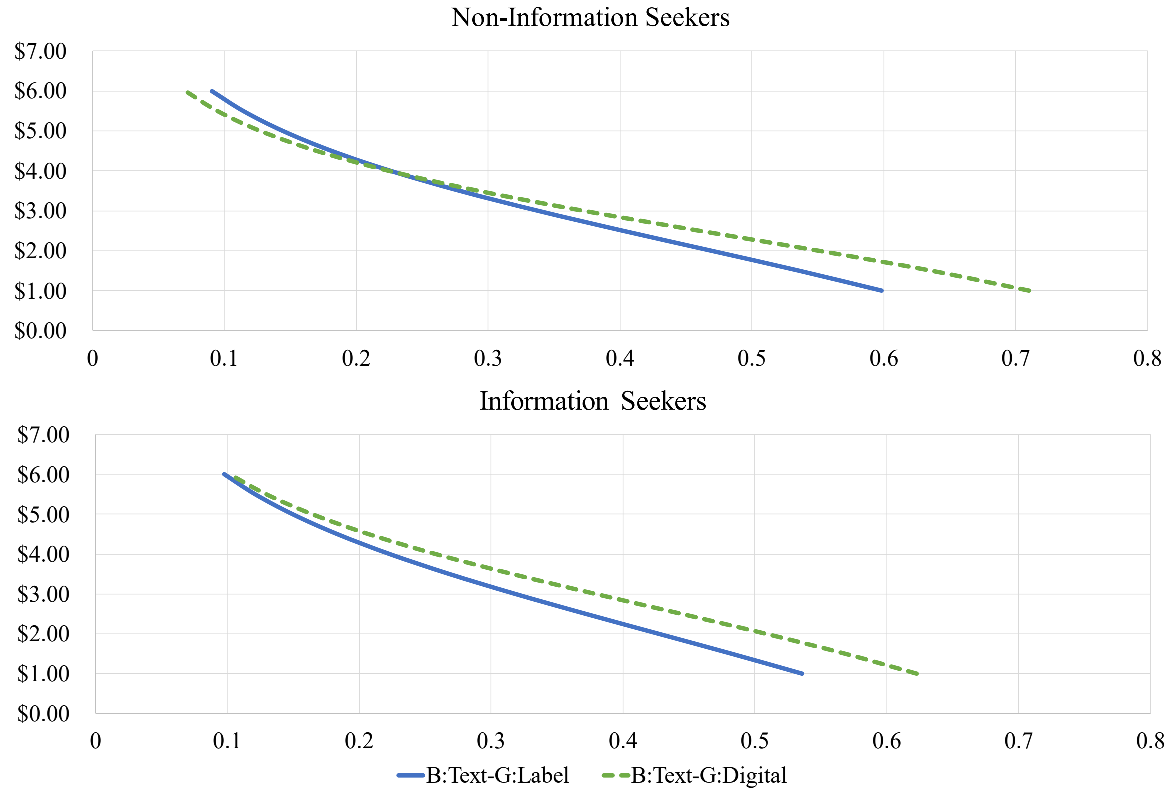
Figure 2. Marginal WTP of the gene-editing vs bioengineered romaine lettuce across treatments, information and non-information seekers



To further look into this issue, we selected two treatments to construct implied demand curves for the bioengineered and gene-edited alternative across both information seekers and non-information seekers: one from the group of four that relies on text and the BE label (B:Text-G:Label) and another from the group including the QR code. (B:Text-G:Digital).These two treatments were selected as we estimated the highest average total WTP for the gene-edited alternative in them. As can be seen in Figure 3, the demand curves for the bioengineered lettuce (Panel A) are much steeper than those for the gene-edited lettuce across treatments (Panel B), indicating that consumers are more responsive to price changes in bioengineered lettuce than gene-edited lettuce. In fact, at prices below $2, the gene-edited alternative is able to capture more than 40% of demand across both information seekers and non-seekers compared to less than 20% for information seekers. This trend may indicate a lower desirability of bioengineered products compared to gene-edited ones. Lastly, we also note that information seekers are generally more willing to pay for gene-edited options compared to non-seekers, but this willingness decreases with higher prices.



Panel A. Implicit demand curve from bioengineered lettuce



Panel B. Implicit demand curve from gene-edited lettuce

Figure 3. Implicit demand curve for the bioengineered and gene-edited lettuce for the B:Text-G:Label and B:Text-G:Digital treatments across information seekers and non-seekers

To further explore information seeking behavior, we investigated the factors that influence consumers decisions to read additional information about the products and scan the QR code for more details about the gene-edited or bioengineered options as part of the NBFDS. We estimated two sets of logit models. In the first set, the dependent variable, named "*Read Information*", is equal to one 1 if consumers opted to read further information about the product before participating in the DCE exercise, and 0 otherwise. In the second set of models, the dependent variable, named "*Scanned QR Code*", is set to 1 if consumers scanned the QR code while responding to the DCE exercise, and 0 otherwise. In both models, the independent variables consist of demographic factors alone in Model 1 (Demographics) and demographic factors plus additional attitudinal variables, including subjective knowledge and policy orientations, in Model 2 (Demographics + Attitudinal)[11]. The results are reported in Table 5.

Table 5. Results from the Logistic Regression

	Read Information (59% of respondents read information)		**Scan QR Code** (23% of respondents scanned the QR code)	
	Demographics	Demographics & Attitudinal	Demographics	Demographics & Attitudinal
Demographics				
Millennial &Younger	0.468***	0.141	1.165***	0.497**
	(0.101)	(0.108)	(0.197)	(0.217)
Female	-0.208**	-0.077	-0.407**	-0.116
	(0.096)	(0.099)	(0.193)	(0.216)
Low Income	0.1000	0.159	-0.538**	-0.400
	(0.118)	(0.121)	(0.218)	(0.248)
College	0.229**	0.190*	-0.007	-0.347
	(0.110)	(0.112)	(0.211)	(0.242)
Children under 12	0.134***	0.060	0.300***	0.131
	(0.052)	(0.053)	(0.084)	(0.088)
Urban	0.362***	0.275**	0.527***	0.302
	(0.109)	(0.112)	(0.190)	(0.221)
Democratic	0.202**	0.121	0.417**	0.219
	(0.096)	(0.101)	(0.186)	(0.213)
Subjective Knowledge (from 1-Not knowledgeable at all to 5-Extremely knowledgeable)				
Difference between BE and GE		0.384***		0.699***
		(0.048)		(0.087)
Base of GE label decision (Average American's View as Baseline)				
Expert Advice		-0.316***		-0.983***
		(0.106)		(0.213)
Treatment Fixed Effects	Not Significant	Not Significant	Not Significant	Not Significant
Constant	-0.131	-0.502**	-2.116***	-2.603***
	(0.197)	(0.237)	(0.344)	(0.420)
Observations	2,003	2,003	758	758

[11] Table A6 in the Appendix reports the aggregated descriptive statistics for the included variables.

Our findings reveal several key insights. First, information-seeking behavior is influenced by both demographic and attitudinal variables in two scenarios: reading general product information to access more detailed information about the product alternatives and using QR codes to access information about gene-edited and bioengineered options. Second, key observations emerge when comparing behaviors between read additional information with the likelihood of scanning a QR code. Millennials and younger consumers demonstrated a stronger inclination towards scanning QR codes, indicating a preference for digital over traditional text-based information. This seeking behavior is not observed for general product information, suggesting potential differences in technology utilization or information-seeking preferences by age. College-educated consumers were less likely than others to seek out additional product information, but education does not significantly differentiate QR code usage. Regarding prior knowledge and attitudinal effects, our results suggest that consumers with higher subjective knowledge about the differences between bioengineered and gene-edited foods were more inclined to both read product information and scan QR codes, with a stronger effect for the latter. This indicates that individuals who feel more informed are likelier to use digital tools to augment their knowledge base, compared to traditional reading. For both types of seeker behavior, consumers who believe that GE decisions should be guided by the average American's view indirectly highlight the need for greater consumer empowerment.

6. Discussion, Policy Implications, and conclusion

Prior research has revealed that, on average, US consumers are willing to pay a premium for both organic (Van Loo et al. 2013) and Non-GMO (McFadden and Lusk 2018) labeled products relative to GM food (see e.g., Onyango and Nayga 2004; Lusk et al. 2005; Costa-Font et al. 2008; Lusk 2011). Our findings align with these trends, thus offering additional insights for producers and marketers in positioning these products and for policymakers in promoting organic agricultural practices.

Our results also indicate a general negative WTP for bioengineered and gene-edited over conventional products, suggesting a lower preference for these as compared to conventional products, corroborating previous research (see e.g., Shew et al. 2018). Our findings also suggest active information seekers tend to be more receptive to gene-edited and bioengineered foods, likely due to their greater exposure to detailed information. This receptiveness makes them ideal targets for educational campaigns about these technologies. Policymakers could facilitate programs that present the benefits and safety of these food products to help alleviate unfounded concerns. This could be done by developing, together with the private industry, claims that state the benefits of these new food technologies. In line with our results, previous studies have shown the positive impact of benefit information on consumer's WTP (see e.g., Kilders and Caputo 2021).

Nonetheless, consumer WTP for bioengineered and gene-edited options varies across treatments, even when comparing bioengineered versus gene-edited lettuce. In cases where these products are labeled with the BE label, there is even a positive WTP especially for gene-edited lettuce. Hence, the way information is presented to consumers can significantly influence their preferences for bioengineered and gene-edited foods, with a noted preference for the BE label over the text and QR code formats. This is consistent with the findings of Kolodinsky and Lusk (2018), who found that mandatory labeling of GM products may reduce consumer aversion to GMOs by giving them a sense of control and improving trust. Therefore,25ituateions where producers must choose between disclosing that a product is gene-edited or bioengineered using the formalized BE label, it may be advantageous for them to opt for the latter.

The fact that consumers prefer the BE label is also denoted by the low rate of QR code scanning suggests that a significant portion of consumers may not be inclined to use QR codes for accessing information about their food products. This has implications for the accessibility and comprehensibility of information for consumers who rely on traditional labeling methods. This finding may provide additional support for ongoing policy debates regarding the use of QR codes for labeling and disclosure of bioengineered or gene-edited foods. For example, the US District Court of Northern California has ruled that allowing bioengineered foods to be labeled only with a QR code is unlawful and that the USDA must instead add additional disclosure options for these foods under the NBFDS (Natural Grocers et al. v. Vilsack et al. 2022). Policymakers may need to consider alternative or complementary methods to ensure that consumers have access to the information they need to make informed choices.

Further differences in consumer valuation for bioengineered versus gene-edited foods are also found among information seekers and non-information seekers. We found that information seekers are willing to pay more for gene-edited and bioengineered products compared to non-information seekers, indicating that access to more detailed information may positively influence their perceptions and acceptance of these technologies. In addition, information seekers display a broader range of WTP for gene-edited and bioengineered foods across different disclosure treatments, suggesting that their preferences can be significantly shaped by how information is presented. When information is delivered via the BE label, they show a positive WTP, which may reflect an appreciation for transparency and ease of access to information. This clear preference for the BE label also points to a broader consumer desire for transparency in food labeling. Policymakers could consider broader legislation that emphasizes transparency even in the case of gene-edited food.

In addition, the findings from our analysis on information-seeking behavior, specifically in the context of reading additional product information and scanning QR codes for gene-edited or bioengineered products, carry significant implications for policymakers, regulators, and industry stakeholders. Some of these implications are based on the demographic effects, while others on more attritional aspects. For example, given the varied preferences across demographics, including gender differences in information-seeking behavior, strategies should aim for inclusivity. This means providing information in multiple formats—both digital and traditional—to ensure broad accessibility. Also, the pronounced inclination of younger demographics to engage with digital information sources, such as QR codes, suggests that regulatory bodies and businesses should develop or improve their digital outreach. This can include more interactive and easily accessible digital content that caters to the tech-savvy generation.

Our research findings also have important implications for the policy debate not only within the US but also in the European Union, where the approach to gene-editing in agriculture and food production has been cautious. However, signs of a more permissive approach are emerging, as evidenced by the European Commission's public consultation on gene-editing in 2020, which received over 20,000 responses (Castaldi 2022). With the EU's strict focus on quality standards and regulatory frameworks as mean of informing consumers about the production of food, our results could offer valuable insights into possible disclosure options that could be employed in other geographic contexts. This could aid in promoting trade and harmonizing regulations between commercial partners. Given the current regulatory framework, producers and processors could capitalize on this fact and avoid disclosing that their products are gene-edited, or alternatively, focus on communicating the benefits of gene-editing to consumers.

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Appendix

Table A1. Socio-demographic Characteristics of the Sample by Treatment

		B:Text-G:Text	B:Label-G:Text	B:Text-G:Label	Combo-Combo	B:Digital-G:Text	B:Digital-G:Label	B:Text-G:Digital	B:Label-G:Digital
Female	1 if respondent is female, 0 otherwise	0.55	0.54	0.56	0.59	0.58	0.57	0.55	0.56
Age	Mean age in years	47	46	48	46	48	47	47	48
College	1 if respondent completed at least a 4 year degree, 0 otherwise	0.41	0.35	0.40	0.36	0.34	0.44	0.41	0.39
Adults	Mean number of adults in household	2.05	2.08	2.03	1.98	1.97	1.97	1.93	1.96
Children	Mean number of children in household	1.62	1.60	1.67	1.67	1.70	1.67	1.61	1.56
Low Income	1 if household income is below X, 0 otherwise	0.79	0.84	0.86	0.83	0.83	0.82	0.85	0.83
QR-Code	1 if respondent scanned the QR-Code, 0 otherwise					0.23	0.26	0.23	0.20
Seeker	1 if respondent accessed the product information, 0 otherwise	0.62	0.59	0.58	0.57	0.55	0.63	0.63	0.57
Number of respondents		258	248	241	246	247	266	240	257

Table A2: Estimates from the MXL Model, Treatment 1~8, Non Information Seekers

		B:Text-G:Text	B:Label-G:Text	B:Text-G:Label	Combo-Combo	B:Digital-G:Text	B:Digital-G:Label	B:Text-G:Digital	B:Label-G:Digital
Alternative Specific Constants									
Conventional									
	mean	4.50*	4.65*	3.80*	5.19*	3.91*	4.68*	4.54*	3.39*
		(0.48)	(0.44)	(0.37)	(0.52)	(0.32)	(0.42)	(0.41)	(0.32)
	St. Dev	2.59*	2.39*	1.91*	2.72*	1.58*	1.88*	1.64*	1.69*
		(0.32)	(0.33)	(0.30)	(0.42)	(0.26)	(0.31)	(0.31)	(0.26)
Organic									
	mean	5.89*	5.53*	4.59*	6.45*	4.33*	5.59*	5.38*	4.11*
		(0.54)	(0.48)	(0.45)	(0.57)	(0.45)	(0.55)	(0.51)	(0.44)
	St. Dev	1.52*	0.94**	1.63*	2.12*	1.97*	1.50*	1.19*	2.02*
		(0.41)	(0.41)	(0.36)	(0.43)	(0.38)	(0.57)	(0.38)	(0.41)
Non-GMO									
	mean	6.10*	5.15*	4.14*	5.65*	3.44*	4.92*	5.23*	4.13*
		(0.53)	(0.48)	(0.50)	(0.61)	(0.45)	(0.61)	(0.52)	(0.45)
	St. Dev	0.69	1.21*	1.69*	2.40*	2.91*	1.86*	0.77	1.71*
		(0.51)	(0.33)	(0.40)	(0.48)	(0.59)	(0.43)	(0.55)	(0.39)
Bioengineered									
	mean	-0.36	1.91*	1.83*	2.57*	3.31*	3.91*	0.71	2.07*
		(1.10)	(0.61)	(0.39)	(0.52)	(0.29)	(0.39)	(0.82)	(0.35)
	St. Dev	3.92*	3.19*	1.15*	1.90*	0.90*	1.51*	2.72*	1.59*
		(0.75)	(0.54)	(0.39)	(0.52)	(0.28)	(0.36)	(0.68)	(0.32)
Gene-Editing									
	mean	-0.37	0.26(0.88)	3.15*	1.77*	2.04*	4.01*	3.86*	2.56*
		(1.03)		(0.38)	(0.77)	(0.38)	(0.41)	(0.42)	(0.33)
	St. Dev	3.60*	3.12*	1.92*	2.69*	1.34*	1.80*	1.71*	1.58*
		(0.59)	(0.67)	(0.34)	(0.63)	(0.38)	(0.36)	(0.32)	(0.31)
Price									
	mean	-1.30*	-1.11*	-0.91*	-1.06*	-1.02*	-1.30*	-1.14*	-0.88*
		(0.11)	(0.10)	(0.09)	(0.10)	(0.08)	(0.11)	(0.11)	(0.08)
	St. Dev	1.30*	1.11*	0.91*	1.06*	1.02*	1.30*	1.14*	0.88*
		(0.11)	(0.10)	(0.09)	(0.10)	(0.08)	(0.11)	(0.11)	(0.08)

Model Statistics								
Choices	582	612	612	636	666	588	528	660
Log-likelihood	-697.7	-736.15	-808.08	-716.56	- 864.33	-751.69	-691.47	-915.83
Parameters	12	12	12	12	12	12	12	12
AIC/N	2.44	2.44	2.68	2.29	2.62	2.59	2.66	2.81

Note: * indicate significance at the 5% level. Standard errors are presented in round brackets

Table A3. Marginal WTP estimates of non-information seekers, segmented by Treatments.

Gene-edited vs…	B:Text-G:Text	B:Label-G:Text	B:Text-G:Label	Combo-Combo	B:Digital-G:Text	B:Digital-G:Label	B:Text-G:Digital	B:Label-G:Digital
Bioengineered	0.00 (1.01) [-1.99, -1.98]	-1.49 (0.85) [-3.16, 0.17]	1.46* (0.46) [-0.56, 2.35]	-0.75 (0.75) [-2.23, 0.72]	-1.25* (0.39) [-2.01, -0.49]	0.08 (0.29) [-0.50, 0.65]	2.77* (0.73) [1.35, 4.19]	0.56 (0.42) [-1.39,0.26]
Conventional	-3.73* (0.85) [-5.40, -2.06]	-3.97* (0.8) [-5.54, -2.39]	-0.72* (0.36) [-1.42, -0.02]	-3.23* (0.76) [-4.72, -1.73]	-1.83* (0.39) [-2.60, -1.06]	-0.51 (0.27) [-1.05,0.02]	-0.60* (0.30) [-1.19,0]	-0.94* (0.39) [-1.70, -0.18]

Note: * indicate significance at the 5% level. Standard errors are presented in round brackets and confidence intervals are presented in square brackets.

Table A4: Estimates from the MXL Model, Information Seekers, Treatment 1~8

		B:Text-G:Text	B:Label-G:Text	B:Text-G:Label	Combo-Combo	B:Digital-G:Text	B:Digital-G:Label	B:Text-G:Digital	B:Label-G:Digital
Alternative Specific Constants									
Conventional									
	mean	2.76*	2.28*	3.49*	3.07*	2.83*	2.47*	4.03*	2.83*
		(0.32)	(0.25)	(0.33)	(0.27)	(0.30)	(0.27)	(0.31)	(0.28)
	St. Dev	2.26*	1.35*	1.82*	1.39*	1.83*	1.54*	1.15*	1.35*
		(0.27)	(0.24)	(0.25)	(0.21)	(0.27)	(0.22)	(0.20)	(0.23)
Organic									
	mean	3.89*	3.53*	4.78*	4.15*	4.43*	3.79*	4.73*	3.99*
		(0.33)	(0.33)	(0.40)	(0.34)	(0.35)	(0.32)	(0.40)	(0.36)
	St. Dev	1.29*	1.75*	1.80*	1.46*	1.23*	1.56*	1.84*	1.68*
		(0.23)	(0.26)	(0.29)	(0.24)	(0.28)	(0.23)	(0.28)	(0.27)
Non-GMO									
	mean	3.72*	3.06*	4.38*	3.47*	3.80*	3.12*	4.49*	3.61*
		(0.34)	(0.34)	(0.41)	(0.36)	(0.39)	(0.34)	(0.41)	(0.36)
	St. Dev	1.30*	1.53*	1.59*	1.39*	1.65*	1.41*	1.89*	1.37*
		(0.25)	(0.31)	(0.36)	(0.21)	(0.31)	(0.25)	(0.29)	(0.28)
Bioengineered									
	mean	1.51*	1.62*	1.82*	1.87*	2.19*	1.95*	2.48*	2.69*
		(0.31)	(0.27)	(0.40)	(0.30)	(0.30)	(0.28)	(0.35)	(0.29)
	St. Dev	1.25*	1.48*	1.56*	1.45*	1.40*	1.46*	1.22*	1.44*
		(0.30)	(0.25)	(0.52)	(0.27)	(0.30)	(0.24)	(0.29)	(0.23)
Gene-Editing									
	mean	1.80*	1.37*	3.14*	1.93*	1.66*	2.67*	3.83*	3.03*
		(0.33)	(0.31)	(0.33)	(0.34)	(0.40)	(0.25)	(0.30)	(0.27)
	St. Dev	1.88*	1.79*	1.78*	1.86*	2.37*	1.46*	0.91*	1.26*
		(0.29)	(0.27)	(0.28)	(0.29)	(0.37)	(0.21)	(0.21)	(0.21)
Price									
	mean	-0.57*	-0.67*	-0.74*	-0.70*	-0.76*	-0.59*	-0.70*	-0.69*
		(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.05)	(0.06)	(0.06)
	St. Dev	0.57*	0.67*	0.74*	0.70*	0.76*	0.59*	0.70*	0.69*
		(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.05)	(0.06)	(0.06)

Model Statistics								
Choices	966	876	834	840	816	1008	912	882
Log-likelihood	-1349.56	-1289.34	-1122.69	-1205.3	-1156.48	-1480.2	-1264.92	-1299.01
Parameters	12	12	12	12	12	12	12	12
AIC/N	2.82	2.97	2.72	2.90	2.86	2.96	2.80	2.97

Note: * indicate significance at the 5% level. Standard errors are presented in round brackets and confidence intervals are presented in square brackets.

Table A5. Marginal WTP estimates of non-information seekers, segmented by Treatments.

Gene-edited vs.….	B:Text-G:Text	B:Label-G:Text	B:Text-G:Label	Combo-Combo	B:Digital-G:Text	B:Digital-G:Label	B:Text-G:Digital	B:Label-G:Digital
Bioengineered	0.53 (0.67) [-0.78, 1.84,]	-0.38 (0.52) [-1.39, 0.64]	1.78* (0.54) [-0.72, 2.83]	0.09 (0.54) [-1.15,0.97]	-0.69 (0.54) [-1.75, 0.37,]	1.21* (0.46) [-0.30, 2.12]	1.93* (0.38) [-1.20, 2.67]	0.50 (0.37) [-0.23, 1.22]
Conventional	-1.69* (0.68) [-3.02, -0.36]	-1.35* (0.49) [-2.31, -0.40]	-0.47 (0.41) [-1.28,0.33]	-1.63* (0.51) [-2.62, -0.64]	-1.53* (0.54) [-2.59, -0.47]	0.33 (0.44) [-0.53,1.19]	-0.28 (0.26) [-0.79,0.24]	0.29 (0.35) [-0.38,0.97]

Note: * indicate significance at the 5% level. Standard errors are presented in round brackets and confidence intervals are presented in square brackets.

Table A6. Variables and statistics of the variables used in the logistic regression

Variable	No. of Obs	Description	Means
Dependent Variables			
Read Extra Information	2,003	=1 if respondent reads extra information; =0 otherwise.	0.594 (0.491)
Scan QR Code	758	=1 if respondent scans the QR code; =0 otherwise.	0.228 (0.420)
Independent Variables			
Demographics			
Millennial &Younger	2,003	=1 if respondent is younger than 43 years old; =0 otherwise.	0.449 (0.498)
Female	2,003	=1 if respondent is female; =0 otherwise.	0.565 (0.496)
Low Income	2,003	=1 if household income is less than $75,000; =0 otherwise.	0.710 (0.454)
College	2,003	=1 if respondent has 4-year college degree and above; =0 otherwise.	0.389 (0.487)
Children under 12	2,003	The number of children under 12 years old in the household, ranging from 0 (no child) to 5 (more than 4 children).	0.638 (0.102)
Urban	2,003	=1 if respondent live in urban area; =0 otherwise.	0.296 (0.456)
Democratic	2,003	=1 if respondent identify him/herself with democratic party.	0.420 (0.494)
Subjective Knowledge			
Difference Between BE and GE	2,003	5-point Likert Scale measured subjective knowledge on the difference between bioengineered food and gene-edited food, from 1-Not knowledgeable at all to 5-Extremely knowledgeable.	2.130 (1.260)
Base of GE Label Decision	2,003		
Expert Advice	2,003	=1 if respondent believe decisions about the labeling of gene-edited food products should mainly be based on views and advice of experts; =0 if respondent believe decisions about the labeling of gene-edited food products should mainly be based on the view of average American.	0.583 (0.493)