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Consumer Preferences for Goat Meat: Findings from a Hypothetical Choice Experiment

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Abstract

While goat meat demand in the United States is increasing, the response in domestic supply is lagging. This consumer study estimates preferences for five product and process attributes: product origin, organic, ethical, grass-fed, and storage condition. From 498 responses, our empirical analysis of choice experiment data revealed significant preferences for organic, grass-fed, and fresh goat meat. Respondents felt favorably toward local and domestic goat meat in comparison to imported goat meat, but indifferent between local and domestic. However, the definition of local mattered. Our findings urge goat meat producers to emphasize process attributes as opposed to locality.

Keywords: choice experiment, consumer behavior, goat, willingness-to-pay

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Introduction

Goat meat demand in the United States is reportedly on the rise, likely in part because goat meat is nutritionally superior to other red meat products, such as beef and pork (Mazhangara et al., 2019; De Silva, Whittaker, and Chidmi, 2024; Hambaryan et al., 2024). However, the domestic supply of goat meat is not increasing (see Figure 1). After peaking in 2008 at 11,133,617 kg, the amount of U.S. goat meat decreased to roughly 8,000,000 kg in 2016, before increasing up to approximately 9,372,000 kg in 2019. Then, the amount decreased for three years and increased again for two years. It appears as if the increase in consumer demand for goat meat is being addressed via imports, which, except for 2008, have exceeded domestic production, comprising over half of the supply.

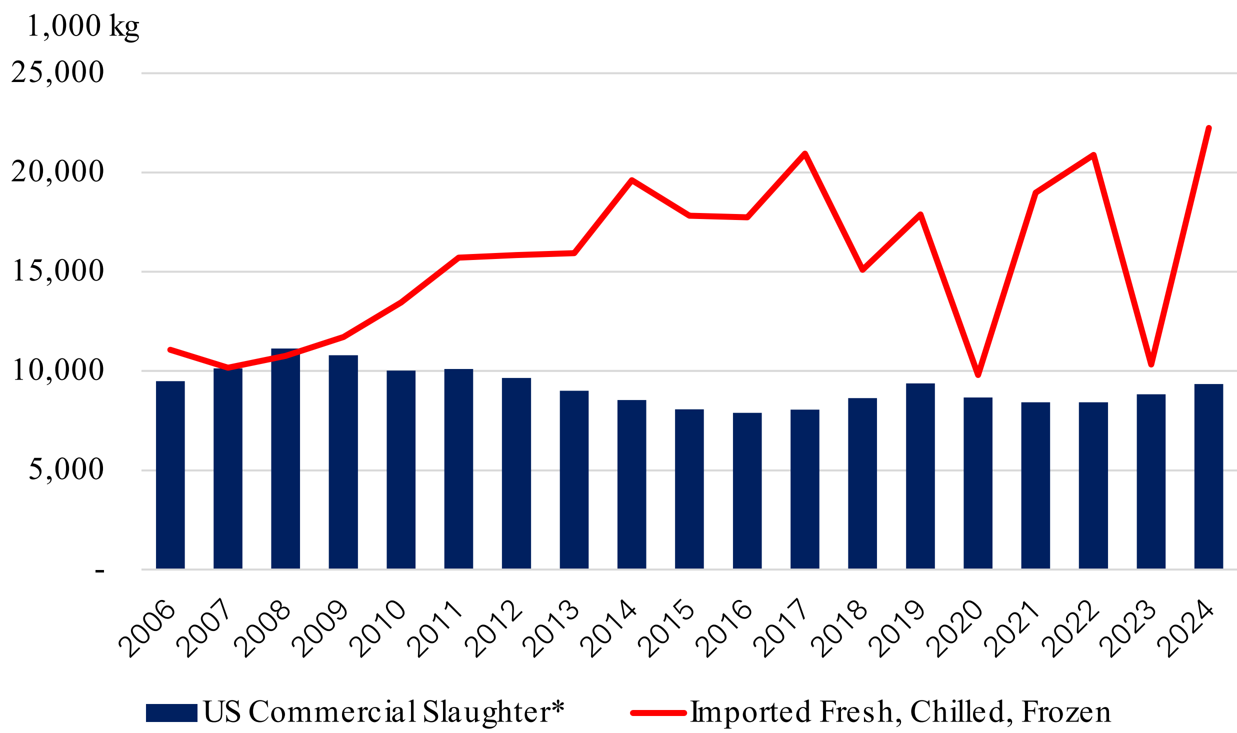

Figure 1. U.S. Goat Meat Supply and Import for the 2010–2024 Period

The increase in consumer demand and the apparent lack of response in producer supply in the United States suggest market opportunities for domestic goat meat producers. However, the number of obstacles to goat meat industry growth is substantial, with deficiencies in processor capacity, marketing system development, and high production cost as the most prominent (Gillespie, Nyaupane, and McMillin, 2013; Hart, Merkel, and Gipson, 2019). Beyond weather variability, goat industry professionals are not sure why goat producers are not increasing herd sizes in response to strong economic conditions (McMillin and Pinkerton, 2022). From a market perspective, among the obstacles is the mixed and scattered evidence of consumer preferences for goat meat attributes. As demonstrated by studies with beef (Grashuis and Su, 2023) and pork consumers (Lusk et al., 2018), knowledge of demand-side preferences is necessary for the supply-side to inform market decisions in terms of production and communication.

To the best of our knowledge, there are only five studies of goat meat consumer preferences in the United States. Ekanem et al. (2013) conducted a hyper-local study of goat meat consumers in Nashville, Tennessee, and measured preferences for storage conditions, cuts, and purchase locations. With emphasis on Arkansas, Georgia, and Missouri, Ibrahim et al. (2020) found that willingness to pay (WTP) for goat meat is in part influenced by age, ethnicity, and education. Similarly, the WTP of goat meat consumers in Florida is correlated with food adventurousness, age, prior goat meat consumption, and ethnicity (Basen et al., 2025). With a representative sample of U.S. meat consumers, Khanal, Dhoubhadel, and Naya Jr. (2025) conducted a choice experiment with price and origin (i.e., domestic, international) as the two attributes of interest and related WTP estimates to information frames and demographic characteristics. The choice experiment design of Hambaryan, Lai, and Kassas (2024) featured more attributes—price, quality, origin, organic, USDA certification—but the sample came from a single state. While each study contributed to our collective knowledge of the U.S. goat meat industry from both producer and consumer perspectives, there are two common limitations: (i) except for Khanal, Dhoubhadel, and Naya Jr. (2025), each of the studies took place in relatively small regions, which limited the ability to generalize observations across the United States, and (ii) the choice experiments by Hambaryan, Lai, and Kassas (2024) and Khanal, Dhoubhadel, and Naya Jr. (2025) omitted ethical production, such as halal and kosher and feed source, as product or process attributes of relevance to goat consumers. Each study adopted a state-level (Hambaryan, Lai, and Kassas, 2024) or country-level perspective (Khanal, Dhoubhadel, and Naya Jr., 2025) of product origin, thus ignoring the possible importance of local production.

Considering the findings above, our objective is to better inform goat meat attribute preferences across the United States. Specifically, our research question is as follows: What are U.S. goat meat consumer preferences for product origin, organic production, ethical production, storage condition, and price? We address the research question with a hypothetical choice experiment with 498 U.S. goat consumers, placing specific emphasis on the product origin attribute, which is found to be of particular relevance to meat products (Balcombe et al., 2016; Dudinskaya et al., 2021). Using a framed approach, we estimate whether preferences for locally produced goat meat are different when labeled as, "from within 100 miles," or ,"from consumers' state," relative to "from the United States," and, "from Australia or New Zealand," while controlling for other common product and process attributes (i.e., organic production, grass-fed production, ethical production, and storage condition). While motivations behind the consumption of local food and drink products are plentiful (Feldmann and Hamm, 2015), such as perceptions of environmental friendliness, freshness, safety, and ethnocentrism, a common definition of local food is still elusive (Cappelli et al., 2022). Empirical distinctions of local food definitions may help address the inefficiencies in local food strategies, policies, and research directions (Brune et al., 2023). Per the analysis of the choice experiment data, local goat meat is unable to capture a price premium relative to domestic goat meat, whether it is labeled as "from within 100 miles" or "from consumers' state." However, U.S. goat meat consumers prefer both local and domestic goat meat to goat meat imported from

Australia or New Zealand. Price premiums for other product and process attributes (i.e., organic and grass-fed production and fresh storage) are similar to those of other meat products.

The article proceeds as follows. In the next section, we present our methodology, including the choice experiment design and procedure, the sample recruitment, and the data analysis method. Then, we present and discuss the results. Finally, we conclude with discussions of implications, limitations, and future research directions.

Methodology

Sample

In July 2025, we contracted with Dynata to recruit a sample of U.S. individuals to participate in an online survey and experiment hosted on Qualtrics. Individuals were required to meet four criteria in order to qualify for participation in our study: (i) be 18 years of age or older, (ii) be the primary or co-primary grocery shopper in their household, (iii) reside in the United States, and (iv) have purchased and consumed goat meat within the past year. Initially, we collected observations from 524 individuals. However, we eliminated observations from 26 individuals who failed one or more of five attention check questions (Paas and Morren, 2018). The decrease in sample size presented a tradeoff in terms of statistical power and data quality. In Table 1 we report the summary statistics of the demographic characteristics of our sample. The average respondent is young (40 years), male (74%), and highly educated (88% have more than a high school degree). However, our sample is not representative of the U.S. population in terms of age, gender, or education, which is not surprising as goat consumers in the United States generally have a different demographic profile (Knight et al., 2006; Khanal et al., 2025). The location of the sample is much more balanced as a third of the sample is from the West U.S. Census Region, 30% from the South, 22% from the Northeast, and 15% from the Midwest.

Table 1. Summary Statistics of Sample Demographic Characteristics

Demographic Characteristic	**Mean**	**Median**	**S.D.**
Age (years)	39.56	40.00	11.57
Male	0.74	1.00	0.44
Education level			
Less than high school	0.00	0.00	0.06
High school	0.07	0.00	0.26
Some college	0.05	0.00	0.22
2-year college degree	0.04	0.00	0.19
4-year college degree	0.42	0.00	0.49
Master’s degree	0.34	0.00	0.47
Doctoral degree	0.04	0.00	0.21
Professional degree	0.03	0.00	0.17
Employment			
Full-time	0.72	1.00	0.45

Table 1 (cont.)

Demographic Characteristic	Mean	Median	S.D.
Part-time	0.08	0.00	0.27
Other	0.20	0.40	0.00
Income ($1000)	96.82	95.00	37.65
Household size	3.76	4.00	1.09
Ethnicity			
White	0.69	1.00	0.46
Asian	0.11	0.00	0.31
Black	0.12	0.00	0.33
Latino	0.03	0.00	0.18
Other	0.04	0.20	0.00
Location			
West	0.33		0.47
South	0.30		0.46
Midwest	0.15		0.37
Northeast	0.22		0.41

Tables 2–3 report summary statistics in terms of purchase frequency, purchase location, cut preference, and attribute importance. Most of the respondents purchase goat meat weekly (42%) or monthly (43%), which indicates our sample is composed of experienced goat meat consumers. The meat store is the most popular outlet to purchase goat meat (74%), followed by the grocery store (64%) and the butcher (46%). The leg (75%), the shank (61%), and the shoulder (59%) are the most popular cuts. Taste (4.53/5) and quality (4.51/5) rank as the two most important attributes to our respondents. Of the 25 product and process attributes, only kosher (3.70) and halal (3.38) have a score below 4.

Table 2. Summary Statistics for Purchase Frequency, Purchase Location, and Cut Preference

How frequently do you purchase goat meat?	
At least once a week	0.42
Once a month	0.43
Less than once a month	0.15
Where do your purchase goat meat?	
Meat store	0.74
Grocery store	0.64
Butcher	0.46
Farmers' market	0.34
Direct from a farmer	0.21
Restaurant	0.17

Table 2 (cont.)

What type of goat meat cuts do you purchase?	
Leg	0.75
Shank	0.61
Shoulder	0.59
Loin	0.35
Ground	0.29
Rib	0.16

Table 3. Importance of Goat Meat Product and Process Attributes

Attribute	Average
Taste	4.53
Quality	4.51
Store cleanliness	4.40
Free from pathogens and diseases	4.38
Safety	4.38
Quantity (weight)	4.32
Availability	4.30
Price	4.29
Free from antibiotics and hormones	4.27
Organic/ecological production	4.26
Condition (fresh/frozen)	4.24
Seller reputation	4.21
Fat content	4.19
Protein content	4.19
Grass-fed	4.18
Convenience	4.17
Cholesterol content	4.13
Origin	4.09
Animal welfare	4.06
Bone-in or boneless	4.06
Carbon footprint	4.06
Package	4.06
Biodegradable packaging	4.05
Kosher	3.70
Halal	3.38

Choice Experiment Design

The first step in designing the choice experiment is to select the attributes and the levels (Lizin et al., 2022). As evidenced by the empirical literature on consumer preferences for goat meat

(Hambaryan, Lai, and Kassas, 2024; Basen et al., 2025; Khanal, Dhoubhadel, and Naya Jr., 2025), there is no shortage of product and process attributes of potential relevance. With design complexity and respondent burden in mind, we are guided foremost by supply and demand considerations. As such, we consider both consumer preferences and producer capabilities, where the inclusion or exclusion of each attribute is informed by the question of whether it can be legally and credibly communicated to consumers. Thus, in close consultation with local extension professionals, we include the following list of attributes and levels:

Product origin. There are three levels: (i) Local, (ii) United States, and (iii) Australia or New Zealand. Generally, food consumers have positive preferences for food produced within a local environment (Feldmann and Hamm, 2015). The inclusion of the "Australia or New Zealand" level is in part based on a study by Phelps et al. (2018). Following Dudinskaya et al. (2021), we expect respondents to have a positive WTP for the "United States" level relative to the "Australia or New Zealand" level.

Organic production. There are two levels: (i) Not organic (i.e., conventional) and (ii) Organic. Lu, Gangyi, and Kawas (2010) discussed various opportunities (and challenges) within the organic goat meat industry. Generally, consumption of organic meat is driven by health and environmental considerations (Cordona et al., 2023). Producers must be certified by the U.S. Department of Agriculture to use the "Organic" label. Following Dudinskaya et al.'s (2021) findings, the expected effect of the "Organic" level is positive. The "Organic" level is often associated with the highest price premium among credence attributes (Li and Kallas, 2021).

Ethical production. There are three levels: (i) Conventional, (ii) Halal, and (iii) Kosher. To be clear, there is no label associated with the conventional production method. Instead, there is an absence of the "Halal" level and the "Kosher" level. Regenstein, Chaudry, and Regenstein (2003) noted "excellent opportunities" in the halal market and the kosher market for food producers. Using a sample of Muslim consumers in the United States, Ibrahim (2011) reported a WTP of $0.50/lb. However, according to Dudinskaya et al. (2021), the "Halal" level is expected to be associated with a negative WTP. No WTP for Kosher has been found.

Feed source. There are two levels: (i) Grain-fed or (ii) Grass-fed. The demand for food animals fed with grass as opposed to grain is driven by health and climate change concerns (Klopatek et al., 2022). From experimental evidence, a positive WTP for the "Grass-fed" level is expected (Britwum and Yiannaka, 2019; Lim, Hu, and Nayga, 2021).

Storage condition. There are two levels: (i) Fresh and (ii) Frozen. Freezing meat is sometimes necessary because of product perishability. Generally, frozen meat is discounted by food consumers, even if food safety is the reason (Lambooij et al., 2019).

Price. There are three levels: (i) $5.99/lb, (ii) $7.99/lb, and (iii) $9.99/lb. The range is informed by the weighted averages of goat meat products at the time of the study.[1] Per economic theory, the expected effect of the price attribute is negative.

The full factorial design is composed of 216 (3*2*3*2*2*3) unique product profiles with random attributes. Following Kuhfeld (2010), we generated a fractional factorial design with a D-efficiency score of 100 with 36 product profiles. Subsequently, we created 18 choice scenarios with two product profiles in addition to an opt-out option. We also established two blocks of nine choice scenarios in order to balance statistical power and respondent burden. We randomly assigned respondents to one of the two blocks.

Furthermore, we implemented a framed design to better inform the "Local" level of the product origin attribute. The term "local" is defined by ambiguity and misconception, both in practice and in theory (Dunne et al., 2011; Feldmann and Hamm, 2015; Granvik et al., 2017). We use two frames. In the first frame, the "Local" level is defined as "from within 100 miles." The reason 100 miles is chosen is based on Tran and Su (2023). In this study, we asked consumers to choose the definition of local food based on mileage from 400 miles, 100 miles, and 50 miles. The results found that 100 miles is the most common definition regarding distance by Missouri consumers. In addition, 100 miles is a common conception in the context of the United States (Smith and MacKinnon, 2009; Adalja et al., 2015). In the second frame, the "Local" level is defined as "from [state name]," where the state name is self-reported by the respondents in an earlier question. This is the most popular definition of "Local" in Tran and Su (2023). Here, we take care not to confuse state-level origin with state-sponsored designations (Onken and Bernard, 2010), such as "Kentucky Proud" (Soley, Hu, and Vassalos, 2019) or "Missouri Grown" (Grashuis and Su, 2023). While we expect a price premium for the "Local" level in both frames (Mehrjerdi and Woods, 2024), any difference between "from within 100 miles" and "from [state name]" is considered to be an empirical exercise.

Choice Experiment Procedure

Participants first received an introduction to the purpose of the study. After explaining the attributes and their levels, we demonstrated how to complete an example of a choice scenario (see Table 4). We then presented a cheap talk script with an objective to minimize hypothetical bias (Ladenburg and Olsen, 2014). Subsequently, participants stated preferences for product profiles in nine choice scenarios. Finally, we administered a brief survey to elicit standard demographic characteristics.

Table 4. Example of a Choice Scenario

Attribute	Product 1	Product 2
Origin	Australia or New Zealand	Local
Organic	USDA Certified	No
Production method		Kosher

[1]https://www.ams.usda.gov/market-news/lamb-veal-and-other-meat-reports

Table 4 (cont.)

Attribute	Product 1	Product 2
Feed source	Grain-fed	Grain-fed
Storage condition	Fresh	Fresh
Which product do you prefer to buy? If you do not like either product, then please answer "neither."		
Product 1		
Product 2		
Neither		

Choice Experiment Data Analysis

Empirically, we estimate consumer preferences for goat meat attributes with random utility theory as the foundation. The utility derived from purchasing and consuming a product is determined by a deterministic component from observed attributes and a random component from unobserved attributes (McFadden, 1974). Therefore, the utility individual i derives from product profile j in choice scenario c is defined as

$$U_{ijc} = \beta_i{}' x_{ijc} + \varepsilon_{ijc} \quad (1)$$

where x_{ict} is the vector of observed or revealed attributes to individual i for product profile j in choice scenario c, ε_{ict} is the random term representing the vector of unobserved or unrevealed attributes, and β_i is the vector of unknown parameters to be estimated. It is possible to separate the deterministic part of the utility function $\beta_i x_{ict}$ into price and non-price attributes, which facilitates a random utility model in WTP-space as opposed to preference-space (Train and Weeks, 2005).

In preference-space, WTP values are estimated by dividing coefficients for non-price attributes by the coefficient for the price attribute, which is assumed to represent fixed or non-random preferences. The price coefficient is therefore often modeled with a normal or log-normal distribution, which may facilitate high WTP values as well as long upper tail WTP distributions (Scarpa, Thiene, and Train, 2008). Thus, following other studies in the recent food consumer behavior literature (Areal and Asioli, 2024; Lin, Ortega, and Sun, 2025), we specify WTP-space as opposed to preference-space models to allow distributional assumptions to be placed directly on WTP. Hence, the utility derived by individual i from product profile j in choice scenario c is

$$U_{ijc} = -\gamma_i{}' p_{ijc} + (\gamma_i WTP_i)' x_{ijc} + \varepsilon_{ijc} \quad (2)$$

where p_{ict} is the price of product profile j in choice scenario c, x_{ict} is the vector of observed or revealed attributes to individual i for product profile j in choice scenario c, and WTP_i is the vector of WTP for each non-price attribute in the choice experiment design. The random scalar γ_i is positive and equals θ_i / k_i, where θ_i represents the price coefficient in preference space and k_i corresponds to the scale parameter for individual i. Also, $WTP_i = \delta_i / \gamma_i$ where δ_i is the vector of non-price coefficients in preference space. In econometric form, we translate equation (2) into

$$U_{ijt} = \omega_1' ProductOrigin_{ijt} + \omega_2' OrganicProduction_{ijt} + \omega_3' EthicalProduction_{ijt} + \omega_4' FeedSource_{ijt} + \omega_5' StorageCondition_{ijt} - \omega_6' Price_{ijt} + \varepsilon_{ijt} \quad (3)$$

We estimate equation (3) separately for the respondents in the first frame and respondents in the second frame. We also estimate an interaction model to allow a direct comparison of the WTP for the Product Origin attribute, as in

$$U_{ijt} = \omega_1' ProductOrigin_{ijt} + \varphi_1' ProductOrigin * Treatment + \omega_2' OrganicProduction_{ijt} + \omega_3' EthicalProduction_{ijt} + \omega_4' FeedSource_{ijt} + \omega_5' StorageCondition_{ijt} - \omega_6' Price_{ijt} + \varepsilon_{ijt} \quad (4)$$

The magnitude and the statistical significance of φ_1 indicate the effect of the frame on the WTP for the Product Origin attribute and the "Local" level specifically. As such, the probability of individual *i* choosing product profile *l* in choice scenario *t*, conditional on β_i, is

$$Q_{ilt}(\beta_i) = \frac{e^{-\gamma_i(p_{ilt} + WTP_i' x_{ilt})}}{\sum_{j \in J} e^{-\gamma_i(p_{ijt} + WTP_i' x_{ijt})}} \quad (5)$$

where β_i is the vector of $\gamma_i WTP_i$. The associated log-likelihood function is estimated by means of maximum simulated likelihood, and the standard errors are obtained with 100 bootstraps via the mixlogitwtp command in Stata 17 (Hole, 2007). We specified the distributions for the non-price attributes and the price coefficient as normal and lognormal, respectively.

Results

Table 5 reports the results of mixed logit WTP-space models on the basis of equation (3). Because the models are estimated in WTP-space as opposed to preference space, the means of the coefficients should be interpreted as the change in U.S. dollars per pound of goat meat relative to the base category. The statistical significance of the standard deviations of the coefficients shows whether there is preference heterogeneity for the given attribute.

Table 5. Mixed Logit WTP-Space Model Results by Frame

	Frame 1 (Local is within 100 Miles)		**Frame 2 (Local is in State)**	
Attribute	**Mean**	**S.D.**	**Mean**	**S.D.**
Price	-2.296***	-0.578***	-1.862***	0.761***
	(0.173)	(0.149)	(0.180)	(0.218)
Origin (base = local)				
USA	1.072	-3.901***	0.037	2.432**
	(0.677)	(1.247)	(0.650)	(1.117)
AUS or NZ	-3.362***	4.631***	-2.209***	4.999***
	(0.842)	(1.265)	(0.745)	(0.974)

Table 5 (cont.)

	Frame 1 (Local is within 100 miles)		Frame 2 (Local is in State)	
Attribute	**Mean**	**S.D.**	**Mean**	**S.D.**
Organic production				
(Base = unidentified)				
USDA organic	2.907***	2.788**	3.065***	-2.705*
	(0.689)	(1.297)	(0.752)	(1.433)
Production method				
(Base = unidentified)				
Halal	1.126	-9.949***	-0.364	-6.942***
	(1.102)	(2.195)	(1.016)	(1.883)
Kosher	0.876	-1.147	-2.289**	-2.987***
	(0.660)	(2.001)	(0.891)	(1.055)
Feed source				
(Base = grain)				
Grass	2.347***	-0.977	2.127***	-3.014***
	(0.744)	(1.573)	(0.738)	(0.998)
Storage condition				
(Base = fresh)				
Frozen	-2.206**	-2.576	-4.090***	-1.531
	(0.868)	(1.778)	(0.985)	(1.438)
Opt out	-64.469***	-28.137***	-64.959***	-28.233***
	(11.129)	(6.028)	(13.323)	(6.755)
N	322		176	
n	8,694		4,752	
Chi2	338.66		129.09	
Log likelihood	-2192.97		-1136.75	
p	0.000		0.000	

Note: ***, **, and * denote statistical significance at 99%, 95%, and 90% confidence levels, respectively.
Parentheses contain standard errors.

With respect to the product origin attribute, we do not find a significant difference in the WTP between the "Local" level and the "United States" level in either of the two frames. As such, labeling goat meat as "from within 100 miles" or "from [state]" is the same as "from the United States" in terms of the price point, although the standard deviations indicate significant heterogeneity in the preferences of our respondents. Our base result is in contrast to most of the literature on local food. According to a meta-analysis by Printezis, Grebitus, and Hirsch (2019), the mean price premium for food labeled as "local" is between $1.70/lb and $2.08/lb. However, when adjusting for publication bias, the premium is decreased to $0.29/lb–$0.40/lb. As demonstrated by Davidson, Khanal, and Messer (2024), it is possible for the local label to have a null effect. In any case, there is much variability across products and countries; none of the 35 studies in Printezis, Grebitus, and Hirsch's (2019) meta-analysis had goat meat as the product of interest. Enthoven and Van den Broeck (2021) also claimed that the overall effect of local food production is dependent on the product and the country. Relativity is also important; many of the price premiums for "local" food have been estimated in relation to "non-local" food with no indication of product origin (Malek et al., 2019). In our case, the "Local" level competed with "from the United States" and "from Australia or New Zealand." Imported goat meat is associated with a significant price discount. Relative to the "Local" level, the WTP estimates are -$3.36/lb in Frame 1 when local is defined within 100 miles and -$2.21/lb in Frame 2 when local is defined within state. The result is in line with most other studies in the food consumer behavior literature with respect to country-of-origin labels (Loureiro and Umberger, 2007; Balcombe et al., 2016; Kang et al., 2025).

The results of the interaction model (see Table 6) allow insights regarding relative preferences for the local attribute depending on its definition. When local is defined as "within 100 miles," it is valued at $7.58/lb relative to when it is defined as "from [state]." Generally, our result informs the ongoing discussion about the definition of local food (Enthoven and Van den Broeck, 2021). There continues to be no consensus around the boundaries of local food, whether the measurement is given in distance, ownership, or otherwise (Brune et al., 2023). Our study relates directly to applied investigations by Adams and Adams (2011) and Brune et al. (2023), who measured preferences for two or more definitions of local food. As in our case with goat consumers, a narrower definition of local appears to be of value. We therefore see a demand-driven incentive for producers and other stakeholders to pursue an industry standard or definition of local food. While state-sponsored designations have been prominent (Onken and Bernard, 2010), there is increasingly more empirical evidence to suggest that local food has the capacity to be marketed and communicated differently.

Table 6. Mixed Logit WTP-Space Interaction Model Results

	Mean		**S.D.**	
Attribute	**B**	**S.E.**	**B**	**S.E.**
Price	-2.188***	0.121	0.794***	0.135
Origin (base = local)				
Local * frame 1	7.580***	2.804	-2.952**	1.229
USA	-0.125	0.599	0.038	1.185
USA * frame 1	8.715***	2.828	-2.901	1.556
AUS or NZ	-1.735**	0.691	4.066***	0.728
AUS or NZ * frame 1	6.782**	2.735	-1.548**	0.646
(Base = unidentified)				
USDA organic	2.408***	0.484	1.968***	0.704
Production method				
(Base = unidentified)				
Halal	0.659	0.596	-5.713***	1.340
Kosher	-0.394	0.440	0.603	0.799

Table 6 (cont.)

	Mean		S.D.	
Attribute	**B**	**S.E.**	**B**	**S.E.**
Feed source				
(Base = grain)				
Grass	1.715***	0.485	2.651***	0.519
Storage condition				
(Base = fresh)				
Frozen	-2.926***	0.602	-2.453***	0.795
Opt Out	-79.014***	12.632	40.974***	7.411
N	498			
n	13,446			
Chi2	494.35			
Log likelihood	-3351.61			
p	0.000			

Note: ***, **, and * denote statistical significance at 99%, 95%, and 90% confidence levels, respectively. Parentheses contain standard errors.

As expected, the organic attribute is associated with a significant price premium in both Frame 1 (WTP = $2.91/lb, p = 0.000) and Frame 2 (WTP = $3.07/lb, p = 0.000). Furthermore, there is significant heterogeneity in consumer preferences. Our result corroborates prior findings in the empirical literature on organic meat consumer preferences. For example, the average Italian beef consumer is WTP 26.25 €/kg more for the organic version (Zanoli et al., 2012). In Germany, Risius and Hamm (2017) also estimated high price premiums for organic beef. Across several European Union countries, the organic label captured the second-highest price premium (following product origin) in the context of red meat products (Dudinskaya et al., 2021). With respect to chicken and pork, Möstl, Janssen, and Zander (2025) found a positive WTP for the organic label among German consumers. Arguably, the best comparison to our result is provided by Van Loo et al. (2011), who estimated a price premium of $3.55/lb for chicken breast labeled as USDA Certified Organic. Although the meat product differs—chicken breast compared to goat—the organic label is identical, and the price premium is similar.

Our first indicator of ethical meat production (i.e., halal) is not associated with a significant WTP in either of the two frames. Three studies can shed light on our results. First, Ibrahim (2011) reported a WTP of $0.50/lb of goat meat using a sample of Muslim consumers in Atlanta, Georgia. Second, Dudinskaya et al. (2021) estimated a price premium for halal red meat products in Turkiye but not in six other European Union countries.

Third, using a predominantly Muslim sample in Belgium, Verbeke et al. (2013) estimated a price premium of €0.90/kg in the context of chicken fillet. These results all suggest the price premium for halal food in general or halal meat in particular is contingent on samples or populations of Muslim consumers. Our sample featured only a small proportion of Muslim consumers, which is the likely explanation for our null result. A literature review by Iranmanesh et al. (2022) revealed a need to conduct more research into non-Muslim attitudes toward halal food, which our result supports. Kosher, our second indicator of ethical goat meat production, is associated with no price premium in Frame 1 (WTP = \$0.88/lb, $p = 0.184$) and a significant price discount in Frame 2 (WTP = -\$2.29/lb, $p = 0.010$). It is unclear why there is a difference in consumer preferences across the two frames. Furthermore, to the best of our knowledge, there are no other WTP studies to compare and contrast our WTP estimates for the kosher attribute. Overall, it appears as if halal and kosher attributes may only appeal to goat meat producers when targeting niche markets with ethnic populations.

As expected, the grass-fed attribute is associated with a significant price premium in both Frame 1 (WTP = \$2.35/lb, $p = 0.002$) and Frame 2 (WTP = \$2.13/lb, $p = 0.004$). In the context of meat products, evidence of price premiums for the grass-fed attribute comes exclusively from the beef sector. For example, according to retail data analysis by Wang, Isengildina-Massa, and Stewart (2023), grass-fed beef price premiums are between 48%–193%. Within an experimental setting, Xue et al. (2010) and Lim, Hu, and Nayga (2021) estimated a mean WTP of \$2.00/lb and \$0.75/lb for the grass-fed attribute, respectively. However, not all the evidence is positive. For example, Umberger, Boxall, and Lacy (2009) generally found a price discount for grass-fed beef steak in comparison to grain-fed beef steak, although a segment of their sample awarded a \$0.42/lb premium. Our result serves as economic motivation to goat meat producers to pursue grass-fed practices and certifications. An example could be A Greener World.

The price discount for the frozen storage condition, which is estimated at -\$2.21/lb in Frame 1 and -\$4.09/lb in Frame 2, is also in line with prior evidence in the food consumer literature. For example, Korean grocery shoppers prefer fresh and chilled beef, not frozen beef (Chung, Briggeman, and Han, 2012). Chinese pork consumers also award price premiums to fresh and chilled products (Wang, Xia, and Guan, 2018). Lambooij et al. (2019) also estimated a price discount for frozen meat, even if it is frozen for food safety reasons. The price discount for the frozen attribute is further motivation for goat meat producers to serve local markets; non-local markets may require the product to be frozen to slow or stop perishability.

Conclusion

The findings of our study carry several important implications for industry practitioners and policy makers who are concerned with the development of the U.S. goat meat sector. For producers and marketers, the lack of a price premium for local product origin—regardless of a narrow ("from within 100 miles") or broad ("from [state]") description—suggests that locality does not facilitate a viable strategy for the pursuit of product differentiation. Instead, practitioners should consider attributes with demonstrated value in both hypothetical and non-hypothetical market environments. Organic and grass-fed attributes command price premiums from food consumers, including goat meat consumers, and should therefore be prioritized by producers over product origin.

For policy makers and extension professionals, the results suggest a need to reassess strategies for promoting local food systems, at least in the context of goat meat. While supporting local production is and will be important in the context of (rural) community development, consumer preferences and market developments may not necessarily align with such policy objectives.

Public investment in the goat meat industry should be calibrated to match demand-side signals, which indicates that a greater emphasis on production rather than location is warranted. Outreach and education may help close the gap between local food narratives and consumer valuations, particularly if there are observed or perceived relationships to food safety and product quality.

Although our study contributes to the limited literature on goat meat consumer preferences, there are several weaknesses and limitations to be addressed. First, although our sample is composed of goat consumers across the United States, the online survey format may limit the generalizability of our results, especially to populations with limited access to the internet. Second, the framing of the "Local" attribute as "from within 100 miles" or "from [state]" may not capture the full range of possible definitions consumers attach to locality. Other definitions may have facilitated different interpretations and recommendations. Third, consumer preferences for credence attributes such as ethical production (i.e., halal, kosher) were estimated without considering religious affiliation or cultural identity. Therefore, nuanced preferences within subgroups may have been overlooked.

Considering the various implications and limitations of our study, future research should address further segmentation of food consumer populations with respect to various demographic and psychographic characteristics, such as ethnicity or food neophobia, to help identify niche markets. Field studies and experiments with information frames may help determine if local or ethical attributes are viable economic instruments by means of framing or messaging. Finally, integrating data on costs, input constraints, and certification challenges would bridge the gap between demand-side and supply-side feasibility, thus informing more realistic and actionable recommendations for the goat meat industry.

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Identifying Local Food Customer Segments Using Cluster Analysis

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Abstract

Customers have different motivations for purchasing local foods. A survey of 1,147 Tennesseans identified three customer segments and the motives behind their local food preferences. The three customer segments were: "Local Indifferent" (30.5% of the sample), "Economy Driven" (40.0%), and "Local Enthusiast" (29.5%). Local Enthusiasts agreed more with wanting to purchase local, feeling social pressure to purchase local, and considering Tennessee (TN) products as higher quality, better for the environment, and benefiting the local economy. Ordered probit regressions indicated purchasing frequency, retailer type, and demographics were correlated with the Local Indifferent and Local Enthusiast segments.

Keywords: cluster analysis; factor analysis; *k*-means local; ordered probit model; quality perceptions

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Introduction

Consumer interest and demand for local foods have been increasing due to their perceived benefits (Kumar et al., 2021; Stone et al., 2021). Between 2019 and 2020, U.S. farms saw a 35% increase in direct-to-consumer sales, which reached $10.7 billion (USDA ERS, 2021). During that time, farmers' market sales increased by 11%, sales to restaurants increased by 13%, and sales via farm stores, community supported agriculture (CSAs), and other direct-to-consumer channels increased by 79% (USDA ERS, 2021). Key motivators for local food purchases include higher perceived quality (Costello and Fairhurst, 2002), perceptions of sustainable or environmentally friendly production (Weber and Matthews, 2008; Jia, 2021), supporting the local economy (Robinson and LaMore, 2010; Filipek, 2018), and knowing the farmer or food source (Jia, 2021). Consequently, local origins generate premiums often ranging from 40.4% to 52.5% for growers (Printezis, Grebitus, and Hirsch, 2019), which can offset additional costs associated with local direct-to-consumer sales (Wang and Sun, 2003; Yue and Tong, 2009; Rihn et al., 2016; Printezis, Grebitus, and Hirsch, 2019; He et al., 2020; Liu et al., 2020; Jia, 2021). Although some of the perceived benefits of local foods are uncertain or vary by production contexts (e.g., food security, environmental benefits; see review by Stein and Santini, 2021), customer perceptions of products being locally grown can improve their preferences for local foods, increase quality perceptions, and generate value for the customer (Nie and Zepeda, 2011; Aprile, Caputo, and Nayga, 2016; Kumar and Smith, 2018; Fan, Gómez, and Coles, 2019).

Local product purchasing motivations are not equal across all consumers, as indicated in a review by Jia (2021), who found that different customer segments may have stronger ties to different motivations. Understanding the prevalent motivations of different customer segments in the market has the potential to aid in marketing efforts for local foods (Nie and Zepeda, 2011; Aprile, Caputo, and Nayga, 2016; Kumar and Smith, 2018). Target marketing, where marketing content is tailored to specific groups, could be used to improve marketing effectiveness and efficiency while reducing marketing expenditures (Dibb et al., 2019). Therefore, the goal of this research is to identify customer segments that explain varying consumer preferences for local products. To accomplish this goal, we conduct a study of Tennesseans to determine their attitudes, views, and frequency of purchasing local products. We conduct factor analysis, *k*-means cluster analysis, and estimate an ordered probit regression to isolate customer segments and find purchasing habits, attitudes, and demographics that correlate with varying local food preferences.

Tennessee consumer preferences were studied because the Tennessee Department of Agriculture (TDA) has a Pick TN Products (PTP) program aimed at helping promote sales of local agricultural products (TDA, 2023). State agricultural marketing improvement programs are prevalent in most states and are used to identify products produced or processed in-state and leverage state identity, brand equity, and promotional materials to encourage sales of those items (Onken and Bernard, 2010; Moreno and Malone, 2021). In Tennessee, the Pick TN Products program has low consumer awareness in-state and across the southeast United States (Fife, Secor, and Campbell, 2025). Low brand (e.g., PTP program) awareness negatively impacts product selection and sales (Yasin, Nasser Noor, and Mohamad, 2007; Huang and Sarigöllü, 2012). Currently, there are approximately 2,600 farmers or farm-direct businesses participating in the PTP program who could potentially benefit from greater brand awareness (TDA, 2023). Aligning target marketing content with customer perceptions increases brand awareness and ultimately could lead to additional sales. Consequently, the PTP program could benefit from targeted marketing messages that focus on benefits that align with customer perceptions.

Tennessee is an interesting state to evaluate because in 2020, Tennessee had 1,418 farming operations selling products locally, which generated $31.8 million in sales, with value-added products adding an additional $25.4 million in sales (USDA NASS, 2022). Between 2012 and 2022, Tennessee's population grew 9.2% to over 7 million people (USA Facts, 2025a). Similarly, the U.S. population grew 6.2% during that time (USA Facts, 2025a). Tourism is a very large industry in Tennessee. The state experienced a 14% annual increase from 2021 to 2022, and accounts for 5.8% of Tennessee's GDP ($27.5 billion) (TN Department of Tourist Development, 2023; USA Facts, 2025b). For comparison, the U.S. travel and tourism industry accounted for approximately 3% of the nation's GDP in 2022 (Arcand and Kern, 2024). It is likely that results of this study will be representative of other states because Tennessee's population growth, and the relative size of the Tennessee tourism industry, is similar to national averages.

Previous research has been conducted that evaluated consumer preferences for local foods in Tennessee. For example, Costello and Fairhurse (2002) identified quality as the main driver of purchasing TN products among tourists. Existing literature has found that Tennesseans are willing to pay premiums for local products (Dobbs et al., 2016; Everett et al., 2017; Everett et al., 2018; Merritt et al., 2018; McKay et al., 2019; Jensen et al., 2021). However, no known research has evaluated Tennessee customer segments for local foods. Therefore, this research extends existing literature by identifying unique Tennessee consumer clusters based on their perceptions of local products. It is expected that results of this research would also be beneficial for other states, especially those with similar demographics, that are interested in the characteristics of customer segments that have varying perceptions of local foods.

Methodology

Survey

An online survey was conducted in May 2022 to elicit Tennessee consumer perceptions of in-state products. Prior to data collection, all experimental procedures and protocols were approved by the institutional review board (IRB-21-06725-XM). Qualtrics software was used to implement the survey, and Qualtrics was hired to recruit the participants to complete the approximately 15-minute survey. To qualify for the survey, participants needed to be 18 years old or older, Tennessee residents, and have grocery shopping responsibilities in their households. The survey consisted of several sections, which addressed purchasing behavior (e.g., frequency, retail location, budget), a discrete choice experiment, perceptions of and motivations to purchase local and PTP items, and demographics. In this analysis, the purchasing behavior, perceptions, motivations, and demographic data were used. A total of 1,957 Tennesseans passed the screening questions and participated in the study. However, due to incomplete responses, a total of 1,147 complete questionnaires (58.6% of the sample) were used in this study's econometric analysis. Stata 17 was used to analyze the data.

Factor Analysis

A factor analysis was used to identify the salient constructs defining Tennesseans' preferences for TN products. The factor analysis included 29 statements from the survey instrument that were related to participants' perceptions and motivations for local and PTP purchases (see Table 2 for a list of the 29 statements). Broadly, there were five statements addressing local perceptions, four statements covering social pressures or norms related to buying local, nine Tennessee produce quality perception statements, four perceived environmental benefits of buying TN products statements, and seven perceived economic benefits of buying TN products statements. All constructs included the same 7-point Likert rating scale (level of agreement), where 1 equaled strongly disagree and 7 equaled strongly agree, and were randomized within the question where they were presented. The statements were divided into seven questions and randomized within each question to reduce order bias.

A principal-factor analysis was used to isolate the constructs. The factor analysis reduced the number of unobserved variables (factors) by grouping together variables with a shared variance (Yong and Pearce, 2013). In order to use factor analysis, a minimum sample size of 300 participants is recommended (Comrey and Lee, 1992). Cronbach's alpha was used to test scale reliability and internal consistency, with 0.70 being the minimum acceptable alpha value (Trochim and Donnelly, 2006). The Kaiser criterion identified the number of factors per construct with an Eigenvalue equal to or greater than 1, indicating the presence of a new factor (Braken and van Assen, 2017). Based on these criteria, a total of five factors were identified from the 29 statements (discussed in detail in the results section).

Cluster Analysis

Following the factor analysis, the factors were used in a *k*-means cluster analysis to identify unique customer segments based on Tennesseans' perceptions and motivations for buying TN products. In turn, this information can be used to tailor marketing strategies to engage clusters that may be more likely to purchase those items. Cluster analysis groups individuals of a population into homogenous groups based on similar perceptions, demographics, or other variables (Dibb et al., 2019). This process is advantageous in that these individuals tend to respond similarly to marketing stimuli, which facilitates target marketing, where marketing communications target a specific customer segment. These communications are tailored to that segment to encourage a better response (e.g., engagement, product/brand/advertisement recall, brand loyalty, purchasing behavior) from those customers. Target marketing provides firms with the benefit of more effectively reaching their customers with content that better resonates. This benefit can result in financial and labor resources being more efficiently used when designing marketing communications.

Econometric Analysis

Given that the cluster membership has an observed natural ordering, an ordered probit model was used to address the relationship among the factors, demographics, and cluster membership (Greene and Hensher, 2009). Ultimately, each model estimates how the different factors impact cluster membership to better understand the key drivers of each cluster.

In an ordered probit model, the latent continuous variable y^* underlies the observed ordinal responses (i.e., cluster membership). y^* is a linear combination of observable variables X (i.e., purchasing behavior, demographic variables) with an ε disturbance terms with a normal distribution. Specifically for X variables, the purchasing behavior variables included frequency of TN product purchases (termed "FreqTNpurchase"), percent of grocery budget spent on TN products ("Per_Tngrocery"), if they perceive PTP products local ("PTP_local"), importance of local production ("Local_impt"), distance travelled to purchase PTP products ("distancetraveled_PTP"), and purchase likelihood from retailers (i.e., grocery—"PL_grocery," big box stores—"PL_bigbox," limited assortment stores—"PL_limited assortment," wholesale stores—"PL_wholesale," specialty stores—"PL_specialty," and farm direct sources—"PL_farmdirect). The demographic variables included the participant's age, number of adults in the household, number of children (< 18 years) in the household, gender, education, household income, and area of residency information (i.e., urban, suburban, rural).

For the ordered probit model, let $i = 1,2, \dots, n$ represent the cluster index with three ordered outcomes ($y_i \in [0,1,2]$). Specifically,

$$y_i^* = X_i\beta + \varepsilon_i \tag{1}$$

where y_i^* is the unobserved latent variable and y_i is the observed ordinal variable.

$$y_i = 0 \ \ if \ y_i^* \leq 0 \tag{2}$$

$$y_i = 1 \ \ if \ 0 < y_i^* \leq \mu_1$$

$$y_i = 2 \ \ if \ \mu_1 < y_i^*$$

and μ_1 and β represent parameters to be estimated. Multinomial probit models were also estimated, and the model fit was assessed using the Bayesian Information Criterion (BIC). The ordinal probit models had lower BIC values than the multinomial probit models, indicating better model fit (ordered probit = 1765.085 versus multinomial probit = 1821.045; Mohammed, Naugler, and Far, 2015). Collinearity was tested between the variables in the model using the coldiag2 command in Stata (based on Belsley, Kuh, and Welsch, 1980) with a value of 21.22, where 30 is an acceptable cut-off value (Kim, 2019). Additionally, the mean variance inflation factor (VIF) was estimated at 1.62, indicating low collinearity issues (i.e., < 10 value; Stata, 2024).

Results

Descriptive Statistics

Table 1 summarizes the sample's demographic and purchasing behavior variables. Participants averaged approximately 45 years old and had two adults per household and one child per household. Slightly more than 66% of the sample were female, and 32% had obtained a bachelor's degree or higher at the time of the study. Approximately 27% of the sample lived in urban areas, 31% lived in suburban areas, and 41% lived in rural areas. Their 2021 household income was $63,348. Compared to the Tennessee population, our sample is slightly older and overrepresents females (U.S. Census Bureau, 2021). These inconsistencies are likely attributed to the screening questions at the beginning of the study, where participants less than 18 years old are excluded (census data include children less than 18 years old) and primary grocery shoppers are targeted. Typically, females are the primary grocery shoppers within the household (Van Hove, 2022). Overall, 70% of participants perceived PTP as local and indicated they spend 25.3% of their total grocery dollars (equivalent to $86.30 per month) on Tennessee grocery products. On average, they were willing to drive 14 miles to buy TN products. Their purchase likelihood for TN products was highest in grocery stores, followed by big box stores, limited assortment, wholesale, and specialty stores.

Table 1. Summary Statistics of the Sample

		Total (n = 1,147)		**TN Population 2021**[1]
	Definition	**Mean**	**SD**	**Mean**
Demographic variables				
Age	Age in years	45.480	15.335	38.8 years
Adult	# of adults in household	2.219	1.093	2.52 people per household
Child	# of children < 18 years in household	0.865	1.228	---
Female	1 = female; 0 = otherwise	0.664	0.472	50.9%
Bachelor's degree +	1 ≥ 4-year bachelor's degree; 0 = otherwise	0.321	0.467	29.0%
Income	Household income in 2021	$63,348	54.253	$58,516
Urban	1 = urban resident; 0 = otherwise	0.266	0.442	
Suburban	1 = suburban resident; 0 = otherwise	0.312	0.464	
Rural	1 = rural resident; 0 = otherwise	0.413	0.493	
Purchase variables				
FreqTNpurchase	Frequency of purchasing TN products; 1 = never; 5 = all of the time.	3.397	0.950	
Per_Tngrocery	Percent of grocery budget spent on TN products, 0%–100%	25.349	22.446	
PTP_local	1 = consider Pick TN Product local; 0 = otherwise	0.709	0.455	

Table 1 (cont.)

	Definition	Total (n = 1,147) Mean	SD	TN Population 2021[1] Mean
Local_impt	Importance of local production; 1 = very unimportant; 7 = very important	5.238	1.574	
PL_grocery	Purchase likelihood of Pick TN Products from grocery store[a]	5.473	1.462	
PL_bigbox	Purchase likelihood of Pick TN Products from big box store[a]	5.402	1.490	
PL_limitedassortment	Purchase likelihood of Pick TN Products from limited assortment store[a]	4.831	1.638	
PL_wholesale	Purchase likelihood of Pick TN Products from wholesale store[a]	4.825	1.640	
PL_specialty	Purchase likelihood of Pick TN Products from specialty store[a]	4.677	1.630	
PL_farmdirect	Purchase likelihood of Pick TN Products from farm direct source[a]	5.369	1.548	
Distancetraveled_PTP	Distance traveled (miles) to purchase Pick TN Products goods	14.199	9.373	

Notes: [1]Source: U.S. Census Bureau (2021). [a]1 = very unlikely, 7 = very likely.

Factor Analysis

From 29 perception statements, a total of five factors were generated. Table 2 summarizes the constructs, mean ratings, factors, factor loadings, and Cronbach's alphas for the factors. Factor 1 had a Cronbach's alpha of 0.867 and consisted of five constructs addressing participants' agreement with different local product purchase-related perception statements and is termed "Local Perceptions" (see Table 2). Generally, participants rated, "It is important to be able to purchase my favorite local foods all year long," the highest (mean rating of 5.42), followed by preferring to purchase TN products (mean = 5.28); Pick TN Products having a Tennessee farm connection (mean = 5.25); Tennesseans should buy TN products (mean = 4.81); and frequently seeking TN products (mean = 4.63).

Factor 2 consisted of four statements addressing social pressure to buy local goods and is termed the "Social Pressure" factor (Cronbach's alpha = 0.938). Generally, participants had the highest level of agreement with the statement, "People who are important to me think I should buy locally produced foods" (mean = 4.44), followed by, "People who influence my consumer behavior think that I should buy locally produced foods" (mean = 4.424); "My friends think that I should buy locally produced foods" (mean = 4.424); and "My family thinks that I should be buying locally produced foods" (mean = 4.391) (see Table 2).

Factor 3 addressed perceptions of TN products compared to those from other states and is termed "TN Quality" (Cronbach's alpha = 0.934). The factor included nine statements, with the highest ratings for agreeing that TN products are fresher (mean = 5.621); higher quality (mean = 5.305);

healthier (mean = 5.092); safer (mean = 4.994); exciting (mean = 4.986); more options (mean = 4.979); more available (mean = 4.951); greater shelf life (mean = 4.933); and less expensive (mean = 4.526) when compared to products from other states (see Table 2).

Factor 4 addressed consumer perceptions of TN products compared to products from other states with regard to environmental benefits (termed "TN Environmental"; Cronbach's alpha = 0.918). The factor included four statements, with the greatest level of agreement with TN products are "better for the environment" (mean = 5.293); "more sustainable" (mean = 5.221); "have a lower carbon footprint" (mean = 5.160); and "have lower greenhouse gas emissions" (mean = 5.064) relative to products from out of state (see Table 2).

Lastly, Factor 5 consisted of seven statements related to how TN products could impact the local economy and is termed "TN Economy" (Cronbach's alpha = 0.914). Participants agreed the most with "Compared to products from other states, TN products support local farmers" (mean = 6.15); "Compared to products from other states, TN products help the local economy" (mean = 6.052); "It is important to support our local farmers and our local business community" (mean = 6.006); "Buying TN products is important because it creates more jobs in the local community" (mean = 5.675); "I worry that local farms are going out of business because most food purchased in supermarkets is grown on larger farms across the country" (mean = 5.621); "Buying TN products is important because more of the money stays in the local community" (mean = 5.609); and, "I am willing to pay more for TN products because it helps the local economy" (mean = 5.067) (see Table 2).

Table 2. Perception Statement Means and Factor Loadings Used in a Factor Analysis (n = 1147)

	Total Sample		**Factor Loadings**
	Mean	**Std. Dev.**	**Local Perceptions**
Factor 1. Local perceptions (1 = strongly disagree; 7 = strongly agree)			
It is important to be able to purchase my favorite local foods all year long.	5.442	1.476	0.679
I prefer to purchase products that are produced in Tennessee.	5.275	1.537	0.842
All Pick TN products have a Tennessee farm connection.	5.250	1.474	0.662
Tennesseans should always buy TN products instead of products produced out of state.	4.811	1.712	0.754
I frequently seek out TN products.	4.628	1.791	0.774
Cronbach's alpha			0.867
Factor 2. Social pressure (1 = strongly disagree; 7 = strongly agree)			
People who are important to me think that I should buy locally produced foods.	4.444	1.802	0.922

Table 2. (cont.)

	Total Sample		Factor Loadings
	Mean	**Std. Dev.**	**Local Perceptions**
My friends think that I should buy locally produced foods.	4.419	1.762	0.897
People who influence my consumer behavior think that I should buy locally produced foods.	4.424	1.809	0.821
My family thinks that I should be buying locally produced foods.	4.391	1.856	0.884
Cronbach's alpha			0.938
Factor 3. TN quality (1 = strongly disagree; 7 = strongly agree)			
Fresher	5.621	1.370	0.736
Higher quality	5.305	1.427	0.839
Healthier	5.092	1.457	0.840
Safer	4.994	1.449	0.851
Exciting	4.986	1.492	0.763
More options	4.979	1.429	0.786
More available	4.951	1.549	0.738
Greater shelf life	4.933	1.475	0.784
Less expensive	4.526	1.651	0.705
Cronbach's alpha			0.9343
Factor 4. TN environmental TN products compared to products from other states (1 = strongly disagree; 7 = strongly agree)			
Are better for the environment	5.293	1.428	0.838
Are more sustainable	5.221	1.415	0.819
Have lower carbon footprints	5.160	1.469	0.867
Have lower greenhouse gas emissions	5.064	1.447	0.865
Cronbach's alpha			2.875
Factor 5. TN economy (1 = strongly disagree; 7 = strongly agree)			
Compared to products from other states, TN products support local farmers in the state.	6.146	1.172	0.741
Compared to products from other states, TN products help the local economy.	6.052	1.243	0.760
It is important to support our local farmers and our local business community.	6.006	1.250	0.841
Buying TN products is important because it creates more jobs in the local community.	5.675	1.359	0.865

Table 2 (cont.)

	Total Sample		Factor Loadings
	Mean	**Std. Dev.**	**Local Perceptions**
I worry that local farms are going out of business because most food purchased in supermarkets is grown on larger farms across the country.	5.621	1.447	0.691
Buying TN products is important because more of the money stays in the local community.	5.609	1.423	0.872
I am willing to pay more for TN products because it helps the local economy.	5.067	1.710	0.687
Cronbach's alpha			4.290

Cluster Analysis

The five factors (i.e., local perceptions, social pressure, TN quality, TN environmental, TN economy) were used in a *k*-means cluster analysis. The optimal number of clusters was determined using the Duda-Hart Je(2)/Je(1) values and Calinski and Harabasz pseudo-F index (Stata, 2024). Based on these metrics, three distinct clusters were identified. Cluster 1 included 30.5% of the sample, Cluster 2 had 40.0% of the sample, and Cluster 3 had 29.5% of the sample. Differences in means between clusters were determined using ANOVA and Tukey's honest significance test in Stata (v.17) and are presented in Table 3.

When considering the factors, Cluster 1 rated the five factors the lowest, whereas Cluster 3 rated the five factors the highest, and Cluster 2 was at an intermediate level between the other two clusters (see Table 3). We named the clusters based on their levels of agreement with the different factors. Cluster 1 was named "Local Indifferent" due to their low level of agreement with the different factor constructs of local perceptions, social pressure, TN quality, TN environmental, and TN economy. Cluster 2 was named "Economy Driven" due to their higher level of agreement with the TN Economy factor relative to the remaining factors. Lastly, Cluster 3 was named "Local Enthusiast," given their high agreement with all of the perceived local or TN-specific benefits.

Table 3. Cluster Summary Statistics and Factor Loadings (n = 1147)

	Cluster 1—Local Indifferent (n = 350)[1,2]			Cluster 2—Economy Driven (n = 459)[1,2]			Cluster 3—Local Enthusiast (n = 338)[1,2]		
	Mean	**SD**		**Mean**	**SD**		**Mean**	**SD**	
Demographic variables									
Age	46.446	15.931	a	49.026	15.049	b	39.663	13.306	c
Adult	1.977	0.939	a	2.087	0.947	a	2.648	1.290	b
Child	0.591	0.970	a	0.660	1.081	a	1.426	1.454	b
Female	0.751	0.433	a	0.784	0.412	a	0.411	0.493	b
Bachelor's degree +	0.309	0.463	a	0.281	0.450	a	0.388	0.488	b
Income	48.693	40.650	a	54.624	38.918	a	90.370	71.976	b
Urban	0.197	0.398	a	0.133	0.340	a	0.518	0.500	b

Table 3 (cont.)

	Cluster 1—Local Indifferent (n = 350)[1,2]			Cluster 2—Economy Driven (n = 459)[1,2]			Cluster 3—Local Enthusiast (n = 338)[1,2]		
	Mean	SD		Mean	SD		Mean	SD	
Suburban	0.351	0.478	a	0.355	0.479	a	0.213	0.410	b
Rural	0.429	0.496	a	0.510	0.500	b	0.266	0.443	c
Purchase variables									
FreqTNpurchase	2.851	0.840	a	3.242	0.721	b	4.172	0.830	c
Per_Tngrocery	15.700	16.276	a	21.013	17.630	b	41.228	25.324	c
PTP_local	0.431	0.496	a	0.739	0.440	b	0.956	0.206	c
Local_impt	4.134	1.263	a	5.139	1.362	b	6.515	1.156	c
PL_grocery	4.934	1.467	a	5.959	1.166	b	5.373	1.600	c
PL_bigbox	4.866	1.535	a	5.821	1.248	b	5.388	1.566	c
PL_limitedassortment	4.237	1.603	a	5.144	1.572	b	5.021	1.600	b
PL_wholesale	4.160	1.594	a	5.211	1.535	b	4.988	1.621	b
PL_specialty	4.049	1.572	a	4.937	1.583	b	4.976	1.575	b
PL_farmdirect	4.631	1.562	a	5.828	1.390	b	5.509	1.456	c
Distancetraveled_PTP	10.037	9.175	a	14.336	8.851	b	18.324	8.368	c
Perception factors									
Local purchase	-0.706	0.635	a	0.110	0.581	b	1.287	0.448	c
Social pressure	-0.608	0.745	a	0.013	0.613	b	1.278	0.680	c
TN quality	-0.724	0.597	a	-0.055	0.565	b	1.508	0.498	c
TN environmental	-0.725	0.574	a	-0.008	0.678	b	1.325	0.463	c
TN economy	-0.953	0.732	a	0.326	0.573	b	1.041	0.265	c
% of Sample	30.5%			40.0%			29.5%		

Notes: [1]Significance between clusters was tested using ANOVA and Tukey's honest significance test. Significance is indicated by different letters at the 5% level.
[2]*k*-means cluster analysis was used to form the clusters.

The "Local Indifferent" cluster consists of 30.5% of the sample (n = 350) and had the lowest level of agreement for all five factors (i.e., local purchase, social pressure, TN quality, TN environmental, TN economy), indicating general disagreement with these factors relative to the Economy Driven and Local Enthusiast clusters (see Table 3). Local Indifferent cluster members averaged 46 years old, and 43% lived in rural areas (both age and rural living were intermediate levels between the other two clusters). Household size, gender, education, income, urban residency, and suburban residency were comparable to Economy Driven cluster members, who had two adults and 0.6 children; were 75% female; had a B.S. degree or higher (31%); had an annual household income of $48,693; and lived in urban areas (20%) and suburban areas (35%). Regarding TN product purchasing behavior, the Local Indifferent members exhibited the lowest ratings (relative to the other clusters) in terms of frequency of purchasing TN products, percent of grocery budget spent on TN products, perceiving PTP-logoed products as local, viewing local as important, and having improved purchase likelihood for PTP products at any of the retail outlets. They were also willing to travel the shortest distance to purchase PTP products at 10 miles.

The second cluster ("Economy Driven") consists of 40% of the sample (n = 459), who rated all of the factors (i.e., local purchase, social pressure, TN quality, TN environmental, TN economy) intermediately between the Local Indifferent (lowest ratings) and Local Enthusiast clusters (highest ratings; see Table 3). Members of the Economy Driven cluster indicated agreement with the local purchase factor and TN economy factor. They indicated slight agreement with the social pressure factor and slight disagreement with the TN quality factor and TN environmental factors. Economy Driven cluster members were the oldest participants at 49 years old and had the highest portion of rural residents (51%). Their other demographic variables were comparable to the Local Indifferent cluster. When considering their purchasing variables, they were intermediate between the other two clusters for frequency of purchasing TN products, percent of grocery budget spent on TN products, perceiving PTP as local, the importance of local origins, and the distance they are willing to travel for PTP products (14.3 miles). They were comparable to Local Enthusiasts for their purchase likelihood ratings of PTP products at specialty stores, wholesalers, and limited assortment stores. The Economy Driven cluster had the highest purchase likelihood ratings out of all three clusters for grocery, big box, and farm direct retail outlets, which may indicate an emphasis on availability and convenience for this cluster.

The last cluster ("Local Enthusiasts") consisted of nearly 30% of the sample (n = 338; see Table 3). They agreed with all of the factors (i.e., local purchase, social pressure, TN quality, TN environmental, TN economy) significantly more than the Local Indifferent or Economy Driven clusters. In turn, this cluster was named the "Local Enthusiast" cluster due to this greater agreement. They were the youngest cluster at 39.7 years old and had the lowest portion of members residing in rural communities (26.6%). They also spent the largest portion of their grocery budget on TN grocery products at 41%, or approximately $140 per month. They had slightly larger households than the Local Indifferent or Economy Driven clusters with 2.6 adults and 1.3 children. They also had a lower portion of female respondents at 46% and the highest household income at $83,809. They exhibited the highest ratings for frequency of purchasing TN products, the importance of buying local, willingness to travel for PTP products (18.3 miles), and 96% of the sample perceived PTP as local. Relative to the other two clusters, they had intermediate ratings for their likelihood of purchasing PTP from grocery, big box, and farm direct outlets.

Cluster Membership

Table 4 summarizes ordered probit model estimates and marginal effects to assess the relationship between different purchase and demographic variables with cluster membership as the dependent variable. The results demonstrate that several purchase behavior variables impacted cluster membership. For instance, participants with a higher frequency of purchasing TN products are 7.4% more likely to be in the Local Enthusiasts cluster. As the percentage of the monthly grocery budget spent on TN products increases, the probability of being in the Local Enthusiasts cluster increases by 0.1%. Individuals who perceive PTP-logoed items as local are 13.4% more likely to be in this cluster. There is also a positive relationship between perceiving local production as important and Local Enthusiast membership, at 6.8%. Membership in the Local Enthusiast cluster increases for each purchase likelihood rating increased by 1.1% for specialty stores and 1.4% for the farm direct retail outlets. These findings align with research demonstrating that local food purchasing behavior and attitudes influence food-related cluster membership (Aprile, Caputo, and Nayga, 2016; Kumar and Smith, 2018). Furthermore, local foods are often purchased directly from producers, which can impact local food access and purchasing behavior (Aprile, Caputo, and Nayga, 2016).

Demographic characteristics also impacted cluster membership (see Table 4). Females are 4.7% less likely to be in the Local Enthusiasts cluster. Having a 4-year bachelor's degree or higher decreases Local Enthusiast cluster membership probability by 5.4% and increases the probability of being in the Local Indifferent cluster by 5.6%. For each additional adult and child within the household, the probability of being in the Local Enthusiasts cluster increases by 2.1% and 2.3%, respectively. Compared to rural residents, living in an urban area increases Local Enthusiast cluster membership by 7.5%. As income increases, so does Local Enthusiast cluster membership at 0.1%. Age and suburban residency does not significantly impact cluster membership. Similar to our results, Nie and Zepeda (2011) surveyed U.S. consumers and determined that the number of adults and being female increased local food interest. While counter to our findings, Aprile, Caputo and Nayga (2016) surveyed Italian consumers and found that older, female consumers with lower education levels and intermediate incomes were more likely to be in the Strict Localist cluster. Overall, many studies agree that demographics impact consumers' purchasing behavior for local foods and cluster membership (Nie and Zepeda, 2011; Aprile, Caputo, and Nayga 2016; Kumar and Smith, 2018), but the effect varies across studies, likely highlighting the importance of gaining insights from different locations.

Table 4. Ordered Probit Model and Marginal Effect Estimates Assessing Consumer Characteristics and Perceptions Impacting Cluster Membership

	Ordered Probit Model		**Marginal Effects**					
			Cluster 1—Local Indifferent (30.5% of Sample)		**Cluster 2—Economy Driven (40.0% of Sample)**		**Cluster 3—Local Enthusiast (40.0% of Sample)**	
	Coef.	**Robust SE**	**dy/dx**	**Delta-method SE**	**dy/dx**	**Delta-method SE**	**dy/dx**	**Delta-method SE**
Purchase variables								
FreqTNpurchase	0.370	0.063***	-0.077	0.013***	0.003	0.002	0.074	0.012***
Per_Tngrocery	0.007	0.002**	-0.001	0.001**	0.000	0.000	0.001	0.000**
PTP_local	0.670	0.095***	-0.140	0.020***	0.006	0.004	0.134	0.020***
Local_impt	0.339	0.037***	-0.071	0.007***	0.003	0.002	0.068	0.006***
PL_grocery	0.071	0.039	-0.015	0.008	0.001	0.001	0.014	0.008
PL_bigbox	0.068	0.037	-0.014	0.008	0.001	0.001	0.014	0.007
PL_limitedassortment	0.056	0.031	-0.012	0.006	0.000	0.000	0.011	0.006
PL_wholesale	-0.028	0.031	0.006	0.006	0.000	0.000	-0.006	0.006
PL_specialty	0.056	0.028*	-0.012	0.006	0.000	0.000	0.011	0.006*
PL_farmdirect	0.071	0.032*	-0.015	0.007	0.001	0.000	0.014	0.006*
Distancetraveled_PTP	0.009	0.005	-0.002	0.001	0.000	0.000	0.002	0.001
Demographic variables								
Age	0.003	0.003	-0.001	0.001	0.000	0.000	0.001	0.001
Adult	0.105	0.040**	-0.022	0.008**	0.001	0.001	0.021	0.008**
Child	0.116	0.038**	-0.024	0.008**	0.001	0.001	0.023	0.007**
Female	-0.236	0.088**	0.049	0.018**	-0.002	0.002	-0.047	0.017**
Bachelor's degree +	-0.269	0.087**	0.056	0.018**	-0.002	0.002	-0.054	0.017**
Income	0.002	0.001**	0.000	0.000**	0.000	0.000	0.000	0.000**
Urban	0.374	0.115***	-0.078	0.024***	0.003	0.003	0.075	0.023***
Suburban	0.012	0.094	-0.002	0.019	0.000	0.001	0.002	0.019

Table 4 (cont.)

	Ordered Probit Model		Marginal Effects					
			Cluster 1—Local Indifferent (30.5% of Sample)		**Cluster 2—Economy Driven (40.0% of Sample)**		**Cluster 3—Local Enthusiast (40.0% of Sample)**	
	Coef.	**Robust SE**	**dy/dx**	**Delta-method SE**	**dy/dx**	**Delta-method SE**	**dy/dx**	**Delta-method SE**
Threshold parameters								
1	4.924	0.400						
2	6.724	0.441						
No. of obs.	1,147							
Log pseudolikelihood	-808.571							
Wald Chi2	530.9							
Prob > Chi2	< 0.0001							
Pseudo R2	0.3525							

Note: Single, double, and triple asterisks (***, **, *) indicate significance at the < 0.1%, 1%, and 5% levels.

Discussion and Conclusions

Consumers are interested in and willing to pay premiums for local goods (Printezis, Grebitus, and Hirsch, 2019), which can overcome additional production costs (Liu et al., 2020; Jia, 2021) and aid rural communities (Stein and Santini; 2022). Consumer preferences for local foods have been studied in various states (Yue and Tong, 2009; Rihn et al., 2016). Evidence shows Tennesseans will pay a premium for local or in-state products (Dobbs et al., 2016; Everett et al., 2017; Everett et al., 2018; Merritt et al., 2018; McKay et al., 2019; Jensen et al., 2021). However, no known study has isolated customer segments for those with varying preferences for local foods in Tennessee. Therefore, this study used an online survey to elicit Tennesseans' motivations for purchasing TN products and clustered participants based upon these motivations. Results are likely relevant for other states with similar demographics to Tennessee.

Through factor analysis, key motivations for buying local products included positive perceptions of local products, social pressure to buy local products, and the perception that local products were of superior quality, better for the environment, and helped improve the local economy. Overall, helping the local economy, supporting local farmers and businesses, and creating jobs in the local community (these were the top four statements out of 29 total statements). The next highest rated motivation was the belief that local products were better for the environment, followed by positive perceptions of local products, superior quality, and social pressures. These results align with the literature showing that supporting the local economy motivates local purchases in Michigan (Robinson and LaMore, 2010) and that sustainability and environmental considerations heighten interest in local products (Weber and Matthews, 2008). The local economy focus may also relate to knowing the local farmer or knowing the farm story behind the purchase, which has contributed to consumer interest in local products (see review by Jia, 2021).

Three clusters were identified to explain different customer segment preferences for local: Local Indifferent, Economy Driven, and Local Enthusiasts. Key differences were observed across the three clusters in terms of demographics, purchasing behavior, and the perception factors. The cluster analysis demonstrates that both the Economy Driven and Local Enthusiast clusters exhibited heightened interest in local Tennessee goods and may be actionable targets for focused marketing efforts. Leveraging the PTP-local connection would be of particular interest to the Local Enthusiast cluster. Often, brands are easier to identify and associate easily with key marketing concepts, which is also observed in state marketing programs where states leverage brands to build positive associations and equity (Onken and Bernard, 2010; Moreno and Malone, 2021). Furthermore, frequently purchasing TN products and allocating a larger portion of the grocery budget to TN products are indicative of the Local Enthusiast cluster. Specialty store availability and farm direct options can attract this cluster, especially if they are in close proximity to urban areas (e.g., farmers' markets). Also, showing promotions that encompass consumers who are similar to their own household demographics may be a means of heightening their awareness and engagement (e.g., self-congruity; Liu et al., 2012). Conversely, if one wishes to target the Economy Driven cluster, marketing promotions should focus on the local community benefits, which could heighten consumer interest. Additionally, product availability with retailers that are accessible to rural community members would align with this cluster's needs.

This study provides insights on underlying motivations and drivers that impact preferences for local products among three distinct customer segments. However, several limitations need to be acknowledged. First, this study uses self-reported stated preference data, and real-world behavior may not align with what participants self-report. Similarly, the data were collected using an online survey, meaning hypothetical bias may have occurred. Both of these limitations could be addressed in future work by incorporating scanner data and retail data or intercept methods to test the robustness of the results in a real-world setting.

Finally, another limitation of this study is that it only surveyed Tennessee consumers. However, Tennessee is similar to the national average in terms of tourism as a percentage of GDP and population growth statistics. Therefore, Tennessee customer segments for local products could be similar to those for the rest of the nation, and particularly similar to states with comparable demographics to Tennessee. Nonetheless, future research could use factor and cluster analysis to identify distinct customer segments for local food preferences nationally.

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Consumer Attitude and Willingness to Pay for GM and GE Edible and Ornamental Products: Implications from Choice Experiment and Structural Equation Modeling

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Abstract

Using choice experiments and structural equation modeling, we assess how positive and negative framing of genetically modified (GM) and gene edited (GE) information are associated with consumer attitudes and subsequent willingness to pay (WTP). We find consumer attitudes serve as an essential mediator, connecting information exposure and consumer characteristics to WTP for GM and GE products. Furthermore, the similarities between the WTP for GM and GE edible and ornamental products were identified. Another interesting finding is that information regarding one technology (GM or GE) is associated with attitudes toward the other, but GM information has a stronger information spillover effect on GE than the reverse. This study provides important implications for both policy making and marketing strategies related to GM and GE products.

Keywords: attitude, choice experiment, CRISPR, genetic modified, gene editing, mixed logit model, structural equation modeling, WTP

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Introduction

In recent years, there has been a growing body of literature in consumer behavior examining consumer willingness to pay (WTP) for foods made from genetic modification (GM) and gene editing (GE). For GM products, genes or modified genes are introduced to a crop from any plant or non-plant organism. Different from GM, GE (e.g., CRISPR) makes targeted changes to genes within a crop instead of introducing foreign genes. This distinction has raised questions about whether consumer attitudes toward GE foods are more favorable compared to their attitudes toward GM products (Son and Lim, 2021).

Revealed and stated preference studies have shown that consumers discount the price they are willing to pay for GM foods compared to conventional foods. In other words, consumers are willing to pay price premiums for non-GM alternatives in comparison to GM foods (Kolodinsky, Rose, and Danielsen, 2023). For example, Ortega et al. (2022) found that consumers are willing to pay about 20%–30% more for non-GM foods compared to GM foods. However, this premium is smaller when consumers are informed that the GM product provides benefits such as improved nutrition or taste. Additionally, consumers are more open to GM applications in plants compared to those in animals, and the premium for non-GM is lower for plants compared to animal products (Ding et al., 2023). As GM applications become more widely adopted, these price premiums for non-GM foods start to decrease (Vasquez, Hesseln, and Smyth, 2022), suggesting a gradual increase in consumer acceptance of GM technology. These studies have also shown there exists a substantial segment of consumers who remain unwilling to pay any premium for non-GM, indicating heterogeneity in consumer preferences.

Compared to GM foods, empirical studies have demonstrated that GE foods tend to have higher consumer acceptance in various countries. For instance, Son and Lim (2021) show that Korean consumers have greater acceptance of GE soybean oil compared to the GM counterpart. Similarly, Chinese consumers discount non-GE rice less than non-GM rice, which might reflect lower perceived risks associated with gene editing (Ding et al., 2023). Vasquez, Hesseln, and Smyth (2022) found Canadian consumers express a higher level of trust in GE than GM. These research findings around the globe imply that GE foods have less consumer resistance, which is potentially due to the perceived minor genetic alterations in GE compared to GM foods.

Attitudes As the Mediator between Information and Willingness to Pay

Consumer acceptance and willingness to pay for GM and GE foods are largely dependent on their attitudes toward biotechnology. The Theory of Planned Behavior (TPB) posits that consumer attitudes directly influence purchasing intentions, such as WTP, with knowledge and information serving as antecedents that form attitudes (Ajzen, 1991). Similarly, the Knowledge-Attitude-Practice Model (KAP) suggests that greater familiarity with GM and GE technologies improves attitudes, which in turn impacts WTP (Xie et al., 2024). Risk-benefit perception frameworks further support the mediating role of attitude, indicating that perceived benefits and risks impact consumer attitudes, which ultimately affect WTP (Bredahl, 2001).

Despite these theoretical foundations, few studies have systematically investigated how attitudes mediate the relationship between positive or negative information, knowledge, and WTP, particularly for both GM and GE products. While studies acknowledge the role of demographics in determining consumers' biotechnology acceptance, less attention has been given to how consumer demographics influence WTP indirectly via attitudes.

Information Spillover Effects

Information plays an essential role in influencing consumer attitudes toward technology. Among the aforementioned studies, Ding et al. (2023) showed participants informational videos describing GM versus GE technologies before eliciting WTP for rice; however, they did not include a control group in their analysis of how these videos impacted WTP. Similarly, Vasquez, Hesseln, and Smyth (2022) included explicit definitions of GE versus GM in their survey before eliciting willingness-to-consume responses, but the study did not test the effect of information on consumer valuations. Researchers who have investigated the effect of information on consumers' WTP for GM or GE products found mixed results. For example, Paudel et al. (2023) found that information about GE technology's health and environmental benefits positively impacts U.S. consumers' valuation for GE soybean oil but not for GE apples.

Consumers often form their opinion of one technology by drawing on their existing information or attitudes toward the other, which is often referred to as information spillover or attitudinal spillover effects. Past research has shown spillover effects for various technologies. For example, Akin et al. (2018) found that the risk perceptions of GM products are associated with support for labeling nano-enabled products. Otsuka (2021) surveyed Japanese consumers and found their attitudes toward GE are significantly influenced by their existing attitudes toward GM. Because GM and GE are both biotechnology, information spillover effects are likely to exist. Identifying and understanding the spillover effects shed light on the development of effective programs and strategies that clearly communicate the similarities and differences among technologies for policy makers and industry stakeholders. Effective communication programs minimize consumer misperceptions and help them make informed decisions. However, to the best of our knowledge, no study has systematically investigated the existence and nature of information spillover effects between GM and GE.

Beyond Food: The Perspective of Nonfood Products

Previous studies have extensively investigated consumer WTP for credence attributes in non-food products, such as organic cotton (Hustvedt and Bernard, 2008) and sustainably produced fibers (Ha-Brookshire and Norum, 2011). However, consumer acceptance of GM or GE non-food products is underexplored. This study directly addresses this gap by examining consumer response to GM and GE attributes across food (potatoes) and ornamental crops (petunias). Understanding consumer preference for biotechnology credence attributes in both non-edible products and foods provides valuable insights into the broader acceptance patterns and has important marketing and policy implications. A recent study examined producer responses and adoption intentions toward GE and GM ornamental and food products and showed the importance of producers' considerations related to profitability, risk management, regulatory perceptions, and market access (Abbey et al., 2025). Integrating insights from our consumer study with producer perspectives is very important because aligning the needs, perceptions, and acceptance levels of these two key market stakeholders can facilitate successful market introductions and policy developments for agricultural biotechnology.

Research Objectives

This study aims to fill these knowledge gaps using choice experiments and structural equation modeling (SEM) to analyze the direct and indirect effects of information, demographics, and psychographics on WTP for GM and GE products. By incorporating information treatments, we assess how positive and negative framing of GM and GE information affects consumer attitudes and subsequent WTP and whether there exist any spillover effects of GM information on GE acceptance and vice versa. We also explore how attitude acts as a mediator among information, consumer demographics, technology familiarity or knowledge, and consumer WTP. Furthermore, by comparing consumer attitudes and WTP between food (potatoes) and ornamental plants (petunias), we investigate whether information treatments on GM and GE elicit different levels of acceptance in different product categories.

Methods

Choice Experiments

We used a discrete choice experiment (DCE) to elicit consumer preferences and WTP for GM and GE products. DCEs are widely used to analyze consumer preferences and WTP for products, particularly when real market behavior data are unavailable for novel products (Yue, Hugie, and Watkins, 2012; Zhao and Yue, 2020; Lusk et al., 2022;). In a DCE, participants are presented with hypothetical choice scenarios and are asked to choose their preferred product option. These experiments are grounded in random utility theory, which assumes that consumers derive utility from product attributes and will choose the option that provides the highest utility (McFadden, 1980). By observing choices over various attribute combinations, we can derive the implicit value consumers place on specific attributes (e.g., GM or GE), which allows us to calculate the WTP premiums or discounts for those attributes.

The products we used in the choice experiment were potato (a popular edible crop) and petunia (a widely used ornamental crop). These two products were chosen because there are bioengineered potato and petunia in the marketplace. For example, Innate potato was commercialized by the J.R. Simplot Company and has disease resistance and reduced bruising. The bioengineered “African Sunset” petunia has a novel intense orange color. The potato attributes include plant type (conventional, GM, and GE), acrylamide level (low, medium, and high), non-browning (yes, no) and price ($3.50, $5.00, and $6.50 per 5 lbs). Acrylamide is a toxin that can be lowered using GM or GE. Non-browning is another benefit achieved by biotechnology. The attribute and attribute levels for petunia are plant type (conventional, GM, and GE), blooming time (season long and one month), flower color (novel-orange/blue or standard-purple/pink), price ($4, $6 and $8 per 6 pack).

The price levels were determined by checking the market price for the products in multiple market venues. Other attribute levels were chosen through a comprehensive literature review and by consulting industry experts. We designed the choice experiment to maximize D-efficiency. Each participant completed eight choice scenarios for each product.

To test how different types of information impact consumer choice and WTP, we included different types of information about GM and GE: positive information about GM, positive information about GE, negative information about GM, and negative information about GE (see Appendix). Participants were randomly assigned to read one of these types of information or were assigned to not read any information (control group).[1]

In addition to DCEs, we asked questions eliciting participants' perceived risk versus benefits and their familiarity with and knowledge level of GM and GE before they were assigned to read any information. After the information treatment, we asked a series of questions about participants' views about GM and GE products, the results of which were used to construct participants' latent attitudes toward GM and GE. Furthermore, questions about participants' willingness to take risks, their consideration for future outcomes, level of caring for the environment, if they consider themselves as more liberal or conservative, and demographics were included in the survey. We conducted a pretest of the survey with 50 participants. Based on their responses to the survey, we adjusted the questions and the choice design. Exploratory factor analyses with principal component extraction were conducted for those factors involving multiple questions.

Mixed Logit Model

We employed a mixed logit model to analyze the DCE data. The mixed logit model allows consumers' taste parameter to vary by some underlying distribution. Specifically, individual i is assumed to have a linear utility function as shown in equation (1):

$$U_{ijm} = \boldsymbol{x_{ijm}} \boldsymbol{\beta_i} + \varepsilon_{ijm} \qquad (1)$$

In equation (1), individual i $(i = 1,2, \dots, N)$ chooses alternative j with their preferred option in J alternatives $(j = 1,2, \dots, J)$. The individual needs to make choices for m $(m = 1,2, \dots, M)$ choice scenarios. $\boldsymbol{x_{ijt}}$ denotes a vector of observed product attributes, such as price, GM, and GE, and $\boldsymbol{\beta_i}$ is the random coefficient vector following certain density function $f(\boldsymbol{\beta}|\boldsymbol{\theta})$, where $\boldsymbol{\theta}$ is a vector of the parameters that define the distribution. In this study, we assume the density function $f(\boldsymbol{\beta}|\boldsymbol{\theta})$ follows multivariate normal distribution. So $\boldsymbol{\theta}$ includes the mean vector and a variance matrix of the multivariate normal distribution, with variance matrix assumed to be diagonal. ε_{ijm} is the random error term that follows type I extreme value distribution and is assumed to be independently and identically distributed. y_{ijm} is a dummy variable denoting individual i

[1] In the experiment, we also included a free-choice treatment: Some participants were randomly assigned the option to choose whether to read the information, whereas others were assigned to read it. However, due to the scope of this study, the free-choice treatment was not included in the current analysis; it will be addressed in a separate paper. In this study, all participants who were either assigned to read the information or given the option to choose but ultimately read it were treated as having read the information.

choosing alternative j in choice scenario m. The probability of individual i choosing alternative j in choice scenario m given β_i is then given by equation (2).

$$L_i(\boldsymbol{y_i}|\boldsymbol{x_i}, \boldsymbol{\beta_i}) = \Pi_{t=1}^{T}\Pi_{j=1}^{J}\left[\frac{exp(\boldsymbol{x_{ijm}\beta_i})}{\sum_{l=1}^{J} exp(\boldsymbol{x_{ljm}\beta_i})}\right]^{y_{ijm}} \tag{2}$$

Equation (3) defines the likelihood function.

$$L = \int_{\theta\in\Theta} L_i(\boldsymbol{y_i}|\boldsymbol{x_i}, \boldsymbol{\beta_i})\, f(\boldsymbol{\beta_i}|\boldsymbol{\theta})d\boldsymbol{\beta_i} \tag{3}$$

In equation (3), $f(\cdot)$ is the density function of a normal distribution with parameter $\boldsymbol{\theta} \in \Theta$. The mixed logit models were estimated using Stata 16.

The WTP for attribute *a* is denoted as WTP_a in equation (4).

$$WTP_a = -\frac{\beta_a}{\beta_p} \tag{4}$$

In equation (4), β_a is the marginal utility of attribute a, and β_p is the marginal disutility from price.

Structural Equation Modeling (SEM)

To better understand the factors influencing consumer WTP for GM and GE food and ornamental products, we employed an SEM framework to simultaneously estimate multiple relationships among key variables, including demographics, attitudes, information exposure, prior knowledge, and perceived risks. SEM accounted for these factors' direct as well as indirect effects on WTP.

SEM is a widely used analytical method in consumer behavior research to investigate the complex relationships among beliefs, attitudes, and behavioral intentions. SEM is a multivariate statistical technique that allows researchers to build and test theoretical models involving latent constructs and observed indicators. SEM can simultaneously estimate a network of relationships, for example, how knowledge influences attitude and how attitude in turn impacts purchase intention, all in one model. In recent years, SEM has been employed to test frameworks such as the TPB and the KAP across a variety of contexts. SEM can incorporate measurement models (confirming that survey questions reliably measure the values of interest) and structural models (testing hypothesized causal paths among those latent constructs) within one analysis (Shin et al., 2017).

Some recent research has employed SEM to test conceptual models of what drives consumer attitudes and intentions of GM food. For instance, Ali et al. (2021) conducted a study on trust and risk perception determinants of GM food acceptance in China and the United States. The researchers developed a structural model where institutional trust, technology trust, perceived benefits, and perceived risks were predictors of overall trust in GM foods, which in turn affected acceptance. They found that GM-specific knowledge was a significant positive predictor of trust in GM foods in both samples.

The structure of our SEM analysis was explicitly informed by TPB and KAP. Our model captured the conceptual relationship of consumer attitudes toward GM and GE products, which worked as mediators that transferred the underlying consumer beliefs and knowledge into measurable WTP outcomes. Additionally, we integrated pre-information exposure (knowledge and familiarity) and information treatment effects into our SEM and explicitly modeled those variables as direct antecedents to consumer attitudes. Structuring our SEM framework around these two robust theories provided a clearer theoretical justification for the selected paths and causal relationships.

The mixed logit model and SEM were complementary in studying consumer preferences for GM and GE products. The mixed logit model directly captured consumer preferences and heterogeneity by estimating individual-level WTP values for specific product attributes, including the GM and GE technology attributes. SEM provided deeper insights into how the psychological and demographic factors impacted these WTP estimates. By combining these methodologies, we not only quantified consumer valuation through mixed logit but also explored the underlying attitudinal and psychological factors that influenced these valuations.

Our SEM model consisted of latent constructs estimated using factor analysis: Attitude toward GM (*AttitudeGM*), attitude toward GE (*AttitudeGE*), WTP latent construct (*WTPlatent*) to pay for GM and GE products, trust in others (*TrustOthers*), and consumer tendency to prioritize short-term versus long-term outcomes (*CFC*). The following observed variables were tested in the model: information exposure to positive or negative information about GM and GE (*ReadingPositiveGM, ReadingPositiveGE, ReadingNegativeGM,* and *ReadingNegativeGE*), demographics (Age, Gender, Income, and Education), pre-information risk perception of GM and GE, familiarity with GM and GE before information exposure (*FamiliarGM* and *FamiliarGE*), willingness to take risks (*RiskTaking*), care about environment (*CareEnvir*), and whether participants considered themselves more liberal or conservative (*Conservative*). We aimed to test the following paths: the direct effects of information exposure, risk perception, demographics, and knowledge on attitudes toward GM and GE; the effect of attitudes toward GM and GE on WTP; and the indirect effects of information exposure, risk perception, demographics, and knowledge on WTP, mediated through attitudes toward GM and GE, as shown in Figure 1.

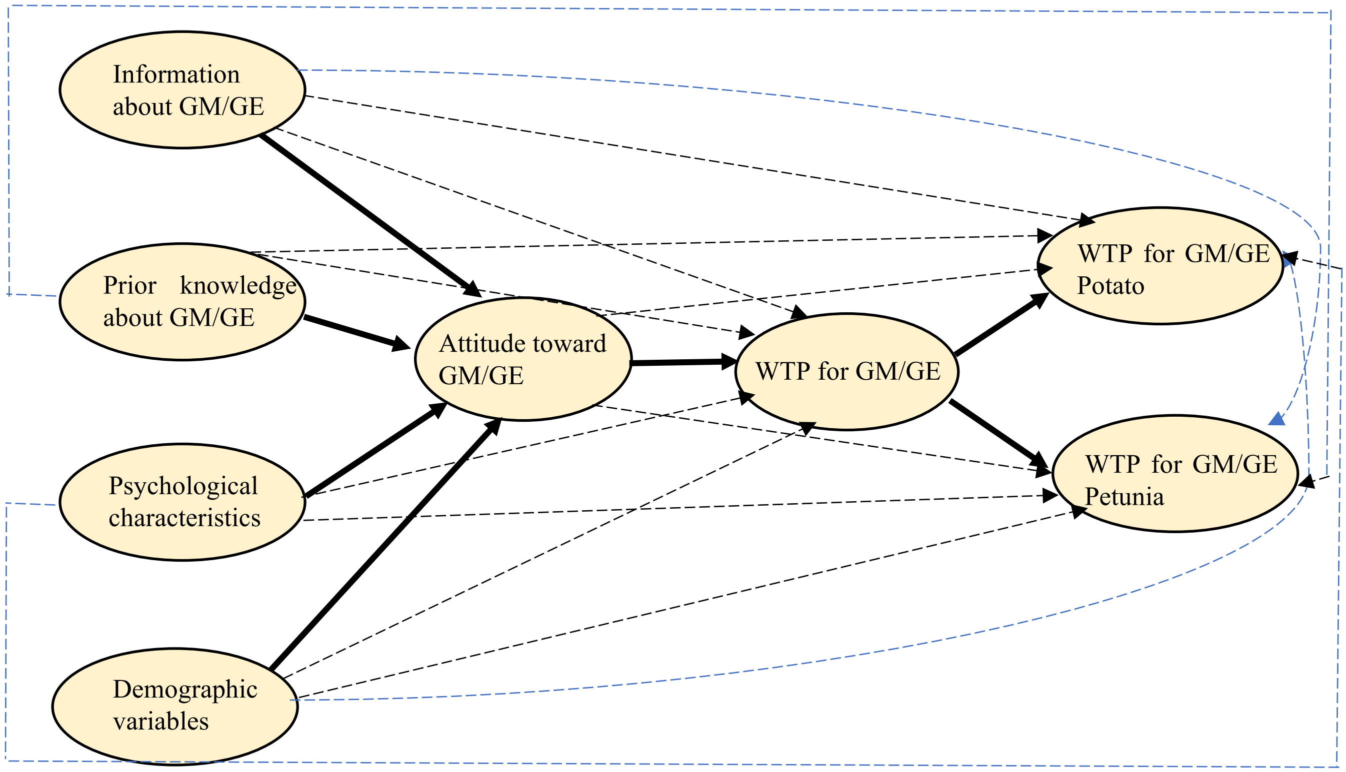

Figure 1. SEM framework (direct effect labeled as solid arrow and indirect effects labeled as dashed arrow)

Results

We collected these data using an online survey through Qualtrics, a professional survey company. To ensure that our sample was representative of decision makers for grocery shopping, we asked a screening question and only those who grocery shopped were allowed to participate. In total, 3,080 consumers from Minnesota, Wisconsin, North Dakota, and South Dakota completed all of the questions used in this analysis. The summary statistics of the demographic and psychographic variables are shown in Table 1. From the table, we can see the average age of participants was 45 years, 29% of participants were male, the income level was $50,000–$74,999, and the average education level was some college.

Table 1. Summary Statistics of Participants' Demographic and Psychographic Variables (N = 3,080)

Variable	Description	Mean	Std. Dev.
Age	Participants' age	45.228	17.444
Gender	Participants' gender: 1 if male, 0 otherwise	0.291	0.454
Income	1 = Less than \$25,000 2 = \$25,000 - \$49,999 3 = \$50,000 - \$74,999 4 = \$75,000 - \$99,999 5 = \$100,000 - \$149,999 6 = \$150,000 - \$249,000 7 = More than \$250,000	2.932	1.486
Edu	1 = Some high school 2 = High school diploma or equivalent 3 = Some college 4 = College degree 5 = Graduate degree	3.359	1.020
RiskTaking	Participants' willingness to take risks:1 = unwilling to take risks and 10 = fully prepared to take risks	5.321	2.172
CareEnvir	Level of agreement with the statement: Taking care of the environment is a big priority to me, 1 = Strongly disagree and 7 = Strongly agree	5.790	1.260
Conservative	Whether participant view him/herself as liberal or conservative, 1 = very liberal and 7 = very conservative	2.922	1.174
FamiliarGM	Participants' familiarity with GM before information treatment, 1 = not familiar at all, 5 = extremely familiar	2.551	1.232
KnowledgeGM	Participants' self-reported knowledge level of GM before information treatment, 1 = not knowledgeable at all, 5 = extremely knowledgeable	2.312	1.094
Prior_riskGM	Participants' perceived risks and benefits of GM before information treatment, 1 = benefit strongly outweighs risk, 5 = risk strongly outweighs benefit	3.227	1.235
FamiliarGE	Participants' familiarity with GE before information treatment, 1=not familiar at all, 5=extremely familiar	1.781	1.063
KnowledgeGE	Participants' self-reported knowledge level of GM before information treatment, 1=not knowledgeable at all, 5=extremely knowledgeable	1.653	0.960
Prior_riskGE	Participants' perceived risks and benefits of GE before information treatment, 1=benefit strongly outweighs risk, 5=risk strongly outweighs benefit	3.247	1.126

We found that before exposure to any information, participants thought they were more familiar with and knowledgeable of GM (mean values were 2.551 and 2.312, respectively) compared to GE (mean values were 1.781 and 1.653, respectively). The perceived risk of GM was about the same as that of GE before information exposure. We conducted *t*-tests between *FamiliarGM* and *FamiliarGE* and found participants' familiarities with GM and GE were significantly different ($p < 0.001$). As expected, participants showed a significantly higher familiarity with GM than GE. This result aligns with the longer history and greater public awareness of GM compared to GE.

Additionally, we divided participants into two groups based on their familiarity with GM or GE, using the mean levels of familiarity as thresholds. *T*-tests were conducted to test whether the perceived risks differed significantly between those who were more familiar with the technology and those who were not familiar. Interestingly, we found familiarity did not significantly impact the perceived risk for GM, but it did significantly impact the perceived risk for GE ($p < 0.001$). One possible explanation for this finding is that GM technology has long been subject to controversial public discourse, and consumers may have developed deeply ingrained risk perceptions that familiarity alone may not effectively reduce. In contrast, GE technology is newer, thus familiarity plays a stronger role in determining consumer risk perceptions. These results indicated the important role of information in consumer acceptance of emergent technologies such as GE.

Mixed Logit Model Results

The results of the mixed logit models are shown in Table 2. Dummy coding was used for categorical variables.

Table 2. Mixed Logit Estimation Results for Potato and Petunia

	Potato	
Variable	**Mean Coefficient**	**Std. Err.**
OptOut	-4.890***	0.093
GM	-0.889***	0.036
GE	-0.789***	0.035
Acrylamide	-0.726***	0.029
Non-browning	-0.123***	0.033
Price	-0.439***	0.012
	Std. Deviation Coefficient	**Std. Err.**
GM	1.384***	0.042
GE	0.905***	0.053
Acrylamide	0.945***	0.022
Non-browning	1.051***	0.038

Table 2 (cont.)

Petunia		
Variable	**Mean Coefficient**	**Std. Err.**
OptOut	-2.402***	0.065
GM	-1.035***	0.044
GE	-0.990***	0.047
Bloomingtime	2.241***	0.055
Color	0.092***	0.035
Price	-0.309***	0.011
	Std. Deviation Coefficient	**Std. Err.**
GM	1.455***	0.049
GE	1.502***	0.050
Bloomingtime	2.473***	0.055
Color	0.764***	0.040

Price Sensitivity and Attribute Preference

For both potato and petunia, the coefficients of price were statistically significant, meaning participants were sensitive to price. For potato, reductions in acrylamide level (−0.726) increased participants' preferences. They did not like the non-browning trait (−0.123). For petunia, longer blooming time and novel color increased purchase likelihood, indicated by significant coefficients (2.241 and 0.092).

Consumer Acceptance of Biotechnology

Coefficients for GM potatoes and petunia were significant and negative, indicating participants did not like GM potatoes and petunia compared to conventional ones. GE potato had slightly less negative preferences compared to GM potato. Using the mixed logit model results, we estimated each individual participant's coefficient for the attributes and then estimated WTP for GM/GE potato and GM/GE petunia by calculating the ratio between an individual's coefficient of GM/GE and the coefficient of price (see Table 3).

Table 3. WTP Estimates for GM Potato, GE Potato, GM Petunia and GE Petunia, Using Conventional as the Base

Variable	**Mean**	**Std. Dev.**
WTPpotatoGM	-2.023	2.390
WTPpotatoGE	-1.820	1.139
WTPpetuniaGM	-3.279	3.152
WTPpetuniaGE	-3.250	3.248

The average WTP estimates were −\$2.023, −\$1.820, −\$3.279, and −\$3.250 for GM potato, GE potato, GM petunia, and GE petunia, respectively. Because the WTP for GM and GE from the same participant might be correlated, we conducted paired *t*-tests between GM versus GE potato and GM versus GE petunia. We found the WTP for GE potato was significantly higher than GM potato, but the WTP for GE petunia was not significantly different from GM petunia. These results indicated participants had a higher level of acceptance of GE than GM for edible products. Consumers may regard GE products as safer or more "natural" than those made from GM technology. This assumption reflects greater trust and potentially less regulatory concern associated with GE edible products compared to GM ones (Son and Lim, 2021; Ding et al., 2023).

Consumer Heterogeneous Preferences

Participants exhibited substantial variability in preferences for all attributes, indicated by significant standard deviations ($p < 0.001$). Figures 2 and 3 show the kernel density of WTP for GM and GE potato and petunia, respectively. One of the most obvious patterns we noted was the bimodal distributions, especially for GM products. A bimodal distribution indicated distinct groups: some participants were more open to GM products, whereas others were strongly against them. This finding highlighted the need for differentiated communication and marketing strategies targeting these segments. For example, groups opposed to GM or GE could be reassured through transparent information on regulatory safety assessments.

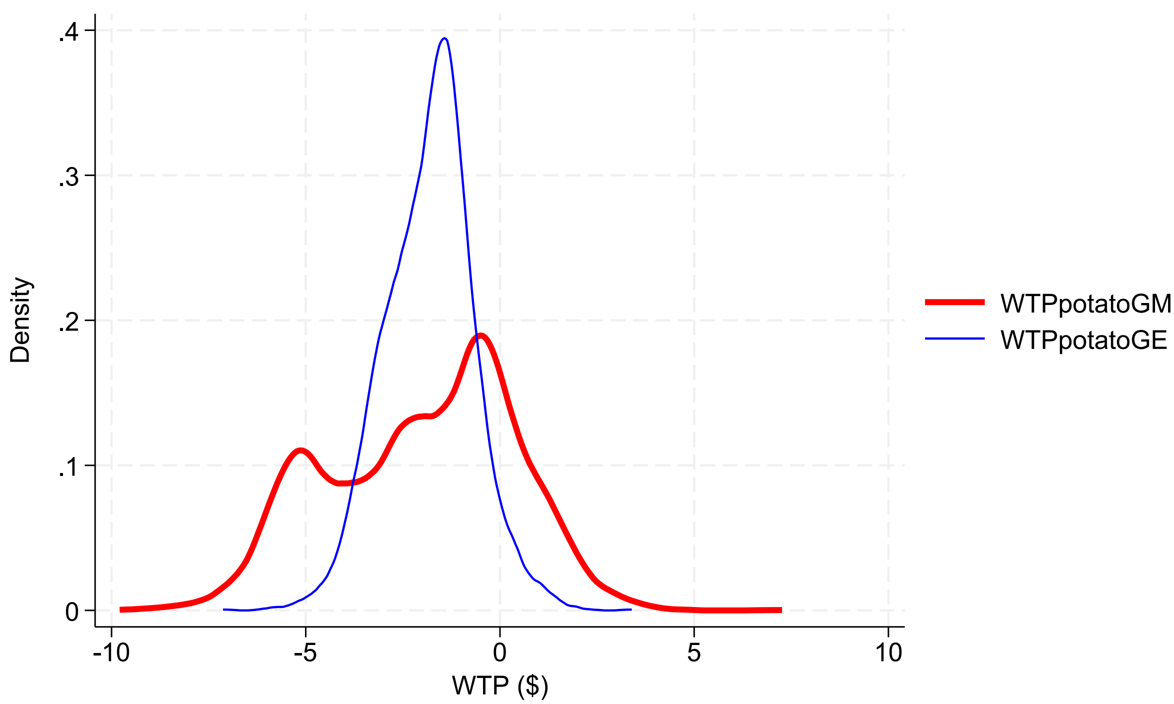

Figure 2. Kernal Density of Participants' WTP for GM and GE Potato

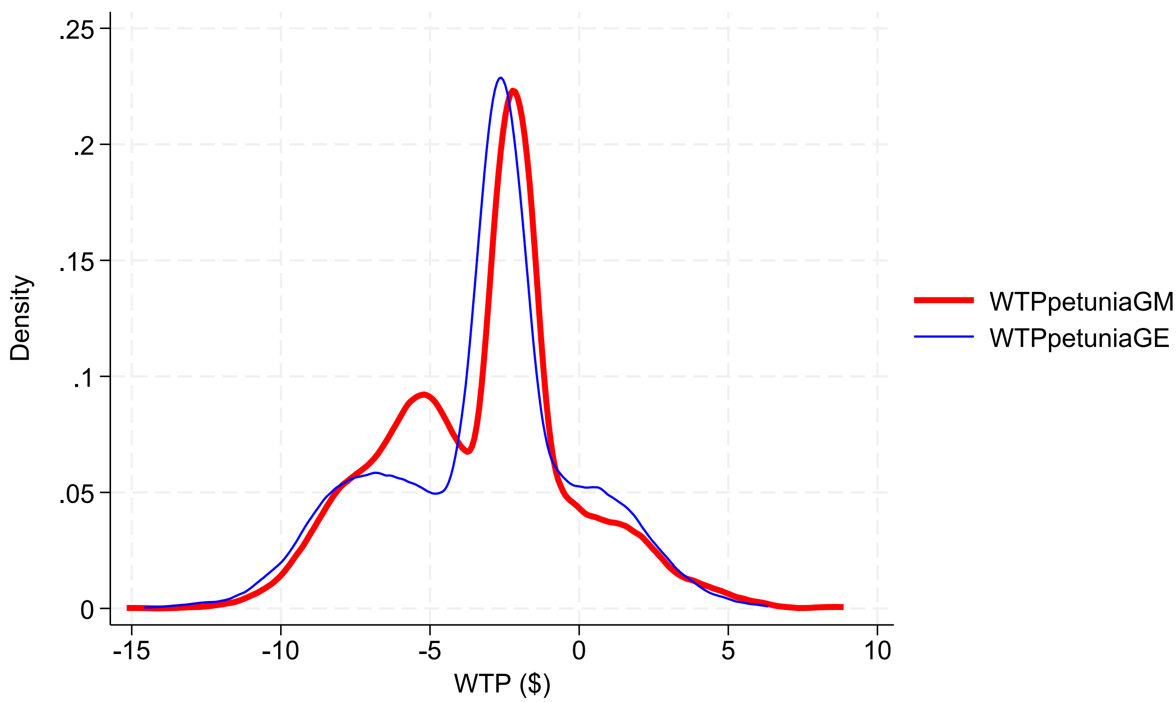

Figure 3. Kernal Density of Participants' WTP for GM and GE Petunia

For potato, the GM potato WTP curve showed bimodality. The GE potato curve was not bimodal and was more sharply peaked, indicating that participants' views of GE potato were less polarized compared to GM potato. The WTP for both GM and GE petunia also showed bimodality but with different intensities. The GM petunia curve had a broader spread, meaning that participants' WTP for GM petunia was more divergent than that of GE petunia. Some participants were neutral or accepting of GM petunia, but others rejected it. In contrast, the WTP for GE petunia was more centered and had a sharper peak near zero. This result implied a more homogeneous preference among participants. The distributions of WTP for GM and GE petunia were similar at the higher peaks. However, the GM curve had a higher secondary peak on the left, which indicated some participants had stronger rejection of GM petunia.

The observed bimodal distributions of WTP for GM products, especially evident in potatoes, suggested distinct consumer groups with different risk tolerance and acceptance levels. The stronger resistance against GM potatoes compared to petunias could be related to direct consumption and perceived health risks associated with edible products. Previous research suggests consumers have lower health concerns about ornamental or non-food crops, which leads to higher acceptance (Chandler and Sanchez, 2012).

Factor Analysis Results

We conducted factor analyses to identify underlying constructs associated with trust of others (*Trustothers*), consideration of future consequences (*CFC*), and attitudes toward GM and GE products (*AttitudeGM* and *AttitudeGE*) after participants read the GM/GE information. Specifically, we conducted exploratory factor analyses. Table 4 shows the questions asked. The table summarizes the mean, standard deviation, and factor loading. We used the threshold of 0.50 to retain the items.

For GM, participants agreed the most with, "I believe GM crops can help with world food security through increased yields," "GM foods need further research before approval for human consumption," and "I am concerned about the long-term environmental consequences of GM crops." For GE, participants agreed most with, "I believe GE crops can help with world food security through increased yields," "I am concerned about the long-term environmental consequences of GE crops," and "I am concerned about the long-term health consequences of GE foods." These results showed participants had reservations about GM and GE products.

The values of the Kaiser-Meyer-Olkin (KMO), which measures sampling adequacy, and Cronbach's Alpha, which measures reliability, are shown in Table 4. The values of Cronbach's Alpha and KMO for *AttitudeGM* were both 0.91. These values were also 0.91 for *AttitudeGE*. The Cronbach's Alpha and KMO values for *Trustothers* were 0.91 and 0.82, respectively, and they were 0.65 and 0.70, respectively, for *CFC*. These values were all close to or above the thresholds for Cronbach's Alpha (0.70) and KMO (0.70) and indicated that reliability and sampling adequacy were acceptable. The *p*-values for Bartlett's Test of Sphericity were significant ($p < 0.001$) for all of the factors, meaning there were appropriate correlations among items for factor analysis.

Table 4. Questions Used in Factor Analysis and the Factor Loadings and Test Statistics for Factor Analysis

Questions	**Mean**	**Std. Dev.**	**Factor Loading**	**Test Statistics**
AttitudeGM				
I believe GM crops can help with world food security through increased yields.	5.054	1.559	0.743	Cronbach's Alpha: 0.91
GM foods need further research before approval for human consumption.	5.366	1.530	-0.626	
Use of GM crops results in less use of pesticides and herbicides.	4.934	1.413	0.603	KMO: 0.91
GM crops have had a positive influence on environmental impacts of farming.	4.561	1.558	0.754	Bartlett's Test of Sphericity: $p < 0.001$
I have no hesitation in consuming GM foods.	4.202	1.880	0.837	
GM foods are safe for human consumption.	4.412	1.686	0.862	
GM technology is outside the natural order.	4.546	1.618	-0.629	
There are no negative consequences of growing or consuming GM crops.	3.193	1.473	0.714	

Table 4 (cont.)

Questions	Mean	Std. Dev.	Factor Loading	Test Statistics
There are no negative consequences of growing GM crops that will not be consumed by people (e.g., ornamental crops).	3.794	1.630	0.624	
I trust government agencies to determine if GM foods are safe (e.g., U.S. Department of Agriculture)	3.975	1.848	0.585	
I am concerned about the long-term health consequences of GM foods.	4.873	1.654	-0.704	
I am concerned about the long-term environmental consequences of GM crops.	5.008	1.595	-0.702	
AttitudeGE				
I believe GE crops can help with world food security through increased yields.	5.047	1.488	0.711	Cronbach's Alpha: 0.91
GE foods need further research before approval for human consumption.	5.311	1.457	-0.669	
Use of GE crops results in less use of pesticides and herbicides.	4.776	1.367	0.620	KMO: 0.91
GE crops have had a positive influence on environmental impacts of farming.	4.436	1.451	0.751	Bartlett's Test
I have no hesitation in consuming GE foods.	3.946	1.812	0.838	of Sphericity:
GE foods are safe for human consumption.	4.166	1.575	0.855	$p < 0.001$
GE technology is outside the natural order.	4.553	1.623	-0.608	
There are no negative consequences of growing or consuming GE crops.	3.372	1.423	0.739	
There are no negative consequences of growing GE crops that will not be consumed by people (e.g., ornamental crops).	3.774	1.572	0.682	
I trust government agencies to determine if GE foods are safe (e.g., U.S. Department of Agriculture).	3.868	1.828	0.541	
I am concerned about the long-term health consequences of GE foods.	4.827	1.623	-0.724	
I am concerned about the long-term environmental consequences of GE crops.	4.875	1.598	-0.720	
TrustOthers				Cronbach's
Most people are basically honest.	4.438	1.563	0.909	Alpha: 0.91
Most people are trustworthy.	4.369	1.543	0.928	KMO:0.82
Most people are basically good and kind.	4.745	1.427	0.898	Bartlett's Test of Sphericity: $p < 0.001$
Most people are trustful of others.	4.344	1.434	0.799	

Table 4 (cont.)

Questions	Mean	Std. Dev.	Factor Loading	Test Statistics
CFC				Cronbach's Alpha: 0.65 KMO: 0.70 Bartlett's Test of Sphericity: $p < 0.001$
I consider how things might be in the future and try to influence those things with my day to day behavior.	5.196	1.231	0.569	
Often I engage in a particular behavior in order to achieve outcomes that may not result for many years.	4.679	1.407	0.567	
I only act to satisfy immediate concerns, figuring the future will take care of itself.	3.512	1.581	-0.808	
My behavior is only influenced by the immediate (i.e. a matter of days or weeks) outcomes of my actions.	3.545	1.631	-0.814	
My convenience is a big factor in the decisions I make or the actions I take.	4.595	1.432	-0.559	

Note: In the factor analysis, the threshold for item retention is 0.50.

SEM Results

Direct and Indirect Influences on WTP

The SEM results, as shown in Tables 5.1 and 5.2, provided detailed insights into the factors associated with participants' attitudes and WTP for GM potato and GM petunia. *AttitudeGM* was significantly associated with WTP for GM petunia and GM potato. Specifically, a strong positive relationship was observed between *AttitudeGM* and the latent WTP construct (*WTPlatent*), with a highly significant coefficient (1.134). *AttitudeGE* also had a significantly positive relationship with the latent WTP construct for GE products.

Table 5.1. SEM Estimation Results for GM Products-Direct effect

	Variable	Bootstrap Coefficient	Bootstrap Std. Err.
Structural	WTPlatent		
	AttitudeGM	1.134***	0.050
Measurement	WTPpetuniaGM		
	WTPlatent	1(constrained)	
	WTPpotatoGM		
	WTPlatent	1.072***	0.048
Structural	AttitudeGM		
	ReadpositiveGM	0.468***	0.047
	ReadnegativeGM	-0.348***	0.043
	ReadpositiveGE	0.102**	0.046
	ReadnegativeGE	-0.205***	0.042
	RiskTaking	0.046***	0.007
	CareEnvir	-0.050***	0.014

Table 5.1 (cont.)

	Variable	Bootstrap Coefficient	Bootstrap Std. Err.
	Trustothers	0.136***	0.017
	Age	-0.003***	0.001
	Gender	0.199***	0.034
	Income	0.038***	0.011
	Edu	-0.009	0.015
	FamiliarGM	0.004	0.021
	KnowledgeGM	0.027	0.024
	Prior_riskGM	-0.358***	0.014
	CFC	-0.114***	0.018

Table 5.2. SEM Estimation Results for GM Products—Indirect Effect

	Variable	Bootstrap Coefficient	Bootstrap Std. Err.
Structural	WTPlatent		
	ReadpositiveGM	0.531***	0.059
	ReadnegativeGM	-0.395***	0.053
	ReadpositiveGE	0.115**	0.053
	ReadnegativeGE	-0.232***	0.048
	RiskTaking	0.052***	0.009
	CareEnvir	-0.057***	0.016
	Conservative	-0.060***	0.016
	Trustothers	0.154***	0.020
	Age	-0.003***	0.001
	Gender	0.226***	0.040
	Income	0.043***	0.012
	Edu	-0.010	0.017
	FamiliarGM	0.005	0.023
	KnowledgeGM	0.030	0.028
	Prior_riskGM	-0.406***	0.024
	CFC	-0.129***	0.021
Measurement	WTPpetuniaGM		
	AttitudeGM	1.134***	0.050
	ReadpositiveGM	0.531***	0.059
	ReadnegativeGM	-0.395***	0.053
	ReadpositiveGE	0.115**	0.053
	ReadnegativeGE	-0.232***	0.048
	RiskTaking	0.052***	0.009
	CareEnvir	-0.057***	0.016
	Conservative	-0.060***	0.016
	Trustothers	0.154***	0.020

Table 5.2 (cont.)

	Variable	Bootstrap Coefficient	Bootstrap Std. Err.
	Age	-0.003***	0.001
	Gender	0.226***	0.040
	Income	0.043***	0.012
	Edu	-0.010	0.017
	FamiliarGM	0.005	0.023
	KnowledgeGM	0.030	0.028
	Prior_riskGM	-0.406***	0.024
	CFC	-0.129***	0.021
	WTPpotatoGM		
	AttitudeGM	1.216***	0.035
	ReadpositiveGM	0.569***	0.060
	ReadnegativeGM	-0.423***	0.054
	ReadpositiveGE	0.124**	0.056
	ReadnegativeGE	-0.249***	0.051
	RiskTaking	0.055***	0.009
	CareEnvir	-0.061***	0.017
	Conservative	-0.064***	0.017
	TrustOthers	0.166***	0.021
	Age	-0.003***	0.001
	Gender	0.243***	0.041
	Income	0.046***	0.013
	Edu	-0.011	0.018
	FamiliarGM	0.005	0.025
	KnowledgeGM	0.032	0.030
	Prior_riskGM	-0.435***	0.021
	CFC	-0.139***	0.022
Goodness of Fit Statistics	RMSEA	0.033	
	CFI	0.965	
	TLI	0.944	
	SRMR	0.016	

WTPlatent had a significant positive relationship with WTP for GM petunia (constrained path coefficient = 1) and GM potato (path coefficient = 1.072). A smaller magnitude was observed for GE potato (0.356). The smaller magnitudes for GE potato compared to petunia indicated stronger participant hesitance toward food products made from biotechnology relative to ornamental plants, which is consistent with previous findings showing consumers are more accepting of biotechnology in ornamental plants compared to food products (Chandler and Sanchez, 2012).

The indirect effects showed that information exposure was significantly related to WTP through attitudes. Reading positive GM information had an indirect positive association with WTP (0.531), whereas reading negative GM information was negatively associated with WTP (−0.395). Demographics were also indirectly associated with WTP: Older participants tended to have lower WTP compared to younger ones (−0.003). Participants with higher income (0.043) and being male (0.226) tended to have a positive indirect relationship with WTP. These results aligned with previous literature showing male consumers, younger consumers, and those with higher income are more accepting of GM or GE products (Moerbeek and Casimir, 2005; Cummings and Peters, 2022). Participants' willingness to take risks (*RiskTaking*) had a significant indirect positive relationship with WTP for GM products (0.052). Caring for the environment (*CareEnvir*) had an indirect negative association with WTP (−0.057). Having more conservative views (*Conservative*) was indirectly linked to WTP for GM products in a negative way (−0.060). These indirect effects were similar for the GE model.

Demographic and Psychographic Determinants of Consumer Attitudes

Participants' demographics had significant associations with attitudes toward GM products. Older participants were less likely to have positive attitudes toward GM compared to younger ones (−0.003). Male participants showed more favorable attitudes toward GM than female participants (0.199). Participants with a higher income level also had significantly more positive attitudes compared to those with a lower income level (0.038). Education did not have a significant association with participants' attitudes toward GM.

Regarding participants' characteristics, those who thought the risk of GM technology outweighed the benefit (*Prior_riskGM*) were positively linked to having negative attitudes toward GM (−0.358). Thus, it is important to address risk perceptions proactively through clear communication on safety evaluations and long-term research outcomes of GM technology. Participants who placed more weight on future consequences (*CFC*) held unfavorable attitudes toward GM (−0.114). Additionally, trust in others (*Trustothers*) was associated with GM attitudes in a positive way (0.136). Participants who were more willing to take risks (*RiskTaking*) were significantly likely to have positive attitudes toward GM directly (0.046). These results aligned well with previous research showing consumers with higher trust in others tend to have positive GM attitudes, and individuals with higher risk propensity are likely to have higher acceptance of GM or GE products (Lu, Xie, and Xiong, 2015; Meerza et al., 2024). Caring for the environment (*CareEnvir*) was negatively associated with GM attitudes directly (−0.050), which indicated that participants associated GM products with negative environmental impacts. Conversely, having more conservative views (*Conservative*) was negatively linked to GM attitudes directly (−0.053).

Similar results were observed for the GE model (see Tables 6.1 and 6.2). The only difference we noticed was the significant coefficients of *FamiliarGE* in the GE model and the insignificant *FamiliarGM* in the GM model. This finding echoed our earlier results on participants' familiarity with GM and GE and might reflect differences in public familiarity with the two technologies. As discussed earlier, GM technology has been extensively discussed, and most consumers may have established attitudes regardless of their level of self-reported familiarity. In contrast, GE technology is newer and consumers are less aware of it. Thus, we saw a stronger connection between consumers' self-perceived familiarity and their attitudes. These results indicated that greater familiarity with GE could reduce uncertainty and enhance positive attitudes.

Table 6.1. SEM Estimation Results for GE Products—Direct Effect

	Variable	Bootstrap Coefficient	Bootstrap Std. Err.
Structural	WTPlatent		
	AttitudeGE	1.292***	0.056
Measurement	WTPpetuniaGE		
	WTPlatent	1 (constrained)	
	WTPpotatoGE		
	WTPlatent	0.356***	0.018
Structural	AttitudeGE		
	ReadPositiveGE	0.320***	0.018
	ReadNegativeGE	-0.245***	0.045
	ReadPositiveGM	0.377***	0.042
	ReadNegativeGM	-0.324***	0.046
	RiskTaking	0.058***	0.045
	CareEnvir	-0.065***	0.008
	Conservative	-0.059***	0.014
	Trustothers	0.139***	0.015
	Age	-0.002**	0.018
	Gender	0.166***	0.001
	Income	0.030***	0.035
	Edu	0.004	0.011
	FamiliarGE	0.050**	0.015
	KnowledgeGE	0.004	0.024
	Prior_riskGE	-0.353***	0.027
	CFC	-0.096***	0.015

Table 6.2. SEM Estimation Results for GE Products--Indirect Effect

	Variable	Bootstrap Coefficient	Bootstrap Std. Err.
Structural	WTPlatent		
	ReadPositiveGE	0.413***	0.061
	ReadNegativeGE	-0.317***	0.057
	ReadPositiveGM	0.487***	0.063
	ReadNegativeGM	-0.419***	0.063
	Risktaking	0.075***	0.011
	CareEnvir	-0.084***	0.019
	Conservative	-0.076***	0.019
	TrustOthers	0.179***	0.024

Table 6.2 (cont.)

	Variable	Bootstrap Coefficient	Bootstrap Std. Err.
	Age	-0.003**	0.001
	Gender	0.215***	0.046
	Income	0.039***	0.015
	Edu	0.006	0.020
	FamiliarGE	0.065**	0.031
	KnowledgeGE	0.006	0.035
	Prior_RiskGE	-0.456***	0.029
	CFC	-0.124***	0.023
Measurement	WTPpetuniaGE		
	AttitudeGE	1.292***	0.056
	ReadPositiveGE	0.413***	0.061
	ReadNegativeGE	-0.317***	0.057
	ReadPositiveGM	0.487***	0.063
	ReadNegativeGM	-0.419***	0.063
	Risktaking	0.075***	0.011
	CareEnvir	-0.084***	0.019
	Conservative	-0.076***	0.019
	Trustothers	0.179***	0.024
	Age	-0.003**	0.001
	Gender	0.215***	0.046
	Income	0.039***	0.015
	Edu	0.006	0.020
	FamiliarGE	0.065**	0.031
	KnowledgeGE	0.006	0.035
	Prior_RiskGE	-0.456***	0.029
	CFC	-0.124***	0.023
	WTPpotatoGE		
	AttitudeGE	0.460***	0.019
	ReadPositiveGE	0.147***	0.021
	ReadNegativeGE	-0.113***	0.020
	ReadPositiveGM	0.173***	0.022
	ReadNegativeGM	-0.149***	0.022
	Risktaking	0.027***	0.004
	CareEnvir	-0.030***	0.007
	Conservative	-0.027***	0.007
	TrustOthers	0.064***	0.009
	Age	-0.001**	0.0004
	Gender	0.076***	0.016
	Income	0.014***	0.005
	Edu	0.002	0.011
	FamiliarGE	0.023**	0.010

Table 6.2 (cont.)

	Variable	Bootstrap Coefficient	Bootstrap Std. Err.
	KnowledgeGE	0.002	0.008
	Prior_riskGE	-0.162***	0.019
	CFC	-0.044***	0.021
Goodness of fit statistics	RMSEA	0.029	
	CFI	0.967	
	TLI	0.947	
	SRMR	0.014	

Information Framing and Cross-Technology Spillover Effects

We found that reading positive information about GM had a significantly positive association with attitudes toward GM (0.468), whereas negative information about GM was adversely associated with attitudes (−0.348). Interestingly, we found that reading positive and negative information about GE technologies also had spillover effects on attitudes toward GM. Specifically, reading positive GE information was positively related to GM attitudes (0.102), and reading negative GE information was negatively associated with GM attitudes (−0.205). We observed similar indirect spillover effects from GE information.

We compared the spillover effects of GM and GE information and found that positive GM information had a stronger spillover effect on attitudes toward GE than positive GE information had on attitudes toward GM. Specifically, the results showed that positive GM information had a significantly positive association with attitudes toward GE (0.377) at the 1% significance level, but positive GE information had a smaller (0.102) and less significant effect on GM attitudes at the 5% significance level, which indicated that when participants read positive information about GM, they were more likely to generalize their positive perception to GE. In contrast, learning about the benefits of GE did not lead to a positive increase in GM attitudes that was as strong. This asymmetry may arise from differences in how these technologies are perceived: GM technology has existed for decades and many consumers have established skepticism about it, whereas GE is often framed as a more precise and "natural" innovation. As a result, positive information about GM may increase the credibility of biotechnology, but the impact of GE-related information on GM remains relatively limited.

A similar asymmetry was observed for negative information effects. Negative GM information was negatively associated with attitudes toward GE (−0.324), but negative GE information had a slightly smaller but still significant negative association with GM attitudes (−0.205). This result shows that negative perceptions of GM are more likely to spill over concerns about GE. Participants who were exposed to negative GM information may have associated similar risks with GE products, as they might perceive GE as a subset or improved version of GM. Conversely, negative information about GE, while still harmful to GM attitudes, did not generate an impact that was as large. The stronger spillover effect of GM information onto GE indicated that well-established or familiar biotechnologies significantly impacted perceptions of newer related technologies. Our results mirrored broader research on technology spillover, where consumers rely on established perceptions of GM to frame new technologies like GE, particularly when GM is seen as familiar or controversial (Akin et al., 2018). As a result, positive (and negative) GM information was more strongly associated with GE attitudes than GE information was with GM attitudes, reflecting both asymmetry and anchoring in public perception.

Goodness of Fit of the Models

To test the goodness of fit for the models, we calculated several test statistics. The results for the GM model were as follows: the Root Mean Square Error of Approximation (RMSEA) was 0.033, the Comparative Fit Index (CFI) equaled 0.965, the Tucker-Lewis Index (TLI) was 0.944, and the Standardized Root Mean Squared Residual (SRMR) equaled 0.016. These statistics suggested an excellent goodness of fit for the model. The overall model fit statistics for the GE model were also excellent, with an RMSEA of 0.029, a CFI of 0.967, a TLI of 0.947, and an SRMR of 0.014, indicating strong model specification.

Conclusions and Discussion

Using choice experiments and analysis methods, such as factor analysis, mixed logit models, and SEM, this research studied how information about biotechnology and its key factors were associated with consumer attitudes and WTP for GM and GE potato and petunia. The similarities between the WTP for GM and GE technologies and edible and ornamental products were identified. Based on these results, this study provides several important implications for both policy making and marketing strategies related to GM and GE products.

The findings highlighted that consumer attitudes served as an essential mediator connecting information exposure and consumer characteristics to WTP for GM and GE products. This mediation effect suggests information is associated with purchasing behavior indirectly through consumer attitudes, meaning that information is linked to consumers' underlying attitudes, which in turn is associated with their economic valuations and choices. An important implication for policy makers and marketers is that they might not solely focus on informational content. Instead, they can carefully consider how the provided information influences consumer attitudes, given that attitudes translate strongly and directly into economic decisions. Additionally, understanding consumer demographics and other characteristics (e.g., trust of others, risk preferences, environmental concerns, and political ideologies) is very important because these factors influence attitudes, which subsequently impact WTP.

The significant associations of positive and negative information with attitudes highlighted the important role communication strategies play in shaping consumer underlying attitudes. These results are consistent with previous findings that have shown positive information increases consumers' WTP, but negative information decreases WTP (Lusk and Coble, 2005; Frewer, Howard, and Shepherd, 2013). Therefore, policy makers and suppliers of GM and GE products could provide clear, accurate, and positive information dissemination in order to encourage informed acceptance of GM and GE products among consumers.

An interesting finding was that information regarding one technology (GM or GE) was associated with attitudes toward the other, that is, the information spillover effect (Martin-Collado et al., 2022). We found positive GM information had a positive relationship with consumer perceptions of GE technology and vice versa, suggesting that a positive message of one technology can potentially have broader beneficial impacts. Similarly, negative messages about one technology can possibly be detrimental to the other. This information spillover effect has been observed by other related studies. For example, a recent study on gene-edited meat found that many consumers' views on GE mirrored their stance on GM foods. The observed information spillover effect indicates that it is important to use holistic and well-coordinated communication strategies when introducing new biotechnologies to consumers. Additionally, we found that even though the information about one influenced perception of the other, GM information had a stronger information spillover effect on GE than the reverse.

Because improving consumer attitudes toward GM can significantly enhance attitudes toward GE, positive GM information could serve as a gateway to achieving broader biotechnology acceptance. Because the negative GM information spilled over strongly onto GE attitudes, efforts can be focused on correcting misinformation about GM to indirectly increase the acceptance of GE technologies. If the goal is to increase GE adoption independently of GM, communications could emphasize its differences from GM, particularly in how it is more precise and does not involve transgenic modification.

Consumers showed consistently greater acceptance and higher WTP for GE-edible products compared to GM ones. The results indicate that GE technology may face fewer consumer-related adoption barriers. As mentioned earlier, unlike GM, GE does not involve the introduction of foreign DNA, so consumers might associate GE with a greater sense of naturalness, and thus a lower perceived risk. Risk perception and technological familiarity might impact the perceived "naturalness" and the adoption of GE. Risk perception is consumers' evaluation of the potential risks of a technology. Technological familiarity refers to the extent to which consumers have experience with a technology. Lower risk perception associated with GE technologies may promote moral licensing because consumers feel morally justified by choosing the seemingly "natural" GE products, and thus their caution about GE products' risks is reduced. Similarly, as consumers become more familiar with GE products, the moral licensing effect can be intensified. When consumers believe that GE foods are safe or familiar, they will unlikely try to verify whether these foods are safe. Food safety narratives need to carefully balance GE's benefits with the transparent communication of ongoing food safety research.

We also found consumers were more accepting of GE food products compared to GM products, but their preferences for GM and GE ornamental products were not significantly different from each other. One possible explanation for this finding is that consumers are more cautious about food products because what they eat directly affects their health. As a result, they prefer GE, which is perceived as more "natural" and less risky than GM. Consumers do not directly consume ornamental plants, so the perceived health risks from GM or GE are low. This assumption weakens the concerns about the distinction between GM and GE, leading to similar levels of acceptance. The results imply that marketing strategies of GE foods can focus on their distinction from GM foods, and that premium pricing for GE foods relative to GM counterparts may be feasible. For ornamental crops, marketing should emphasize product attributes (novel color, longer bloom, disease resistance, etc.) achieved by GM or GE rather than the technologies themselves.

We found a significant relationship between demographics (age, gender, income) and attitudes toward GM and GE. Thus, targeted campaigns can effectively reach specific groups. Younger, higher income, and male consumers are more open to these technologies, which is consistent with previous findings (McFadden and Lusk, 2017; Cummings and Peters, 2022). Communications can be developed to target specific demographic segments with less favorable attitudes (e.g., older consumers, lower-income groups, or female in the case of GE) to enhance their acceptance of the technologies.

Furthermore, we found that consumers who focus on future consequences were less inclined to favor GM and GE products, which aligns with findings in behavioral economics that suggest individuals who discount the future heavily may be more responsive to immediate advantages rather than long-term risks (Günden et al., 2024). Since GM and GE crops often provide immediate benefits, such as reduced pesticide use, longer shelf life, better taste, and lower food prices, consumers who regard short-term outcomes as more important may be more willing to trade off perceived risks for short-term gains. For marketing and public communication, emphasizing the short-term, tangible benefits of GM and GE technologies could be an effective way to increase acceptance by present-focused consumers. Framing GM/GE foods around long-term sustainability or global food security will resonate more strongly with future-focused consumers.

Our study had several limitations. First, although potatoes and petunias were both frequently purchased products by consumers, they may still differ widely in consumer familiarity, risk perception, and frequency of purchase. These asymmetries could affect comparability across product categories. Second, participants in our study were from four Midwestern states. The generalization of our results to national or international populations should be made with caution. Further studies can be conducted to validate the applicability of our results to other regions or countries. Third, when we estimated mixed logit model, we assumed normal distribution for the random parameters. We acknowledge that different distribution assumptions might yield different WTP estimates. Lastly, our sample was skewed toward female participants. Including only grocery shoppers in the screening of survey participants that resulted in a sample consisting of more female than male participants. Based on previous research, the majority of grocery shoppers in a household are female (Schaeffer, 2019); most of the plant purchasers are also female (Statista, 2023). From this perspective, our sample is more representative of decision makers for grocery shopping than a gender-balanced sample. However, readers should consider that this demographic distribution may influence our results, particularly because gender significantly affected attitudes and WTP in our analysis.

Due to the scope of this study, we did not conduct subgroup analysis despite some demographic and psychographic variables having significant effects. Further studies could explore how results differ among age, gender, or psychographic groups. Additionally, the significant standard deviation coefficients and the kernel distributions indicated the existence of consumer segments in terms of their attitudes toward GM and GE food or ornamental crops. Our future effort will focus on exploring consumer heterogeneity and consumer segmentation in terms of their preferences for GM and GE ornamental and food crops.

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Appendix

<u>Positive information about GM</u>

How does it work?

- DNA or modified genes are added to a crop from any plant or non-plant organism.
- Adding non-plant genes to a crop triggers a regulatory process.
- In most cases the genes for a new trait may be modified from their original form and may contain more than one modified gene from any organism.

Health and safety

- The US Department of Agriculture (USDA) has determined GM food crops are safe for consumption and the environment.
- The US Environmental Protection Agency (EPA) has determined there are no negative environmental impacts of growing GM crops.
- The US Food and Drug Administration (FDA) has determined GM food crops are safe for consumption and determined GM foods equivalent to conventional foods.
- GM food crops show fewer toxins, carcinogens, and allergens when compared to conventional food crops of the same variety.
- GM foods are grown with less pesticide, herbicide, and fertilizer than conventional foods.
- GM makes food healthier by enhancing nutrients and reducing unhealthy chemicals.

Environment:

- GM crops tolerate drought, frost, and other environmental stressors, making production less uncertain.
- GM crops produce more food with less pesticide, feeding the world's growing population while decreasing the costs to health and environment.
- GM crops that are herbicide-tolerant are grown with less synthetic insecticides using conservation tillage (less or no-till farming) which reduces greenhouse gases and increases soil health.
- The environmental and human health impact of synthetic pesticides can be dramatically lowered using GM crops that produce their own natural pesticides.
- GM crops are grown using less fuel, reducing greenhouse gas emissions and can be used as renewable fuels and biodegradable plastic.
- GM crops can trap carbon capturing CO_2 emissions and increasing soil health.

Business Practices

- GM crops increase yield and profitability for farmers, ensuring food security, and lowering costs to consumers.
- GM crops are used by large and small farms equally providing economic opportunity for all.
- As GM crops are increasingly used and accepted, growers and consumers will share in the economic benefits stimulating creation of even more beneficial crops to increase farm profits while protecting the environment and human health.

Summary

- The benefits of GM crops could save the planet from climate change, make food healthier, and feed the world. Throwing out this technology could be throwing out a brighter future.

- GM crops have been grown and consumed for over 25 years without any significant negative impacts and many benefits.

<u>Negative information about GM</u>

How does it work?

- DNA or modified genes are added to a crop from any plant or non-plant organism.
- Adding non-plant genes to a crop triggers a regulatory process.
- In most cases the genes for a new trait may be modified from their original form and may contain more than one modified gene from any organism.

Health and safety

- Despite government approval of some GM food crops for farming and consumption, many possible health issues related to growing and consuming GM food crops have not been and cannot be fully tested.
- Genetic modification can create unintentional issues like producing new allergens, toxins, or carcinogens in food.
- There may be unanticipated health side effects that cannot be predicted or easily and quickly detected.
- Bacteria exposed to GM plants could acquire antibiotic resistance that could in turn spread antibiotic resistant bacteria.
- While the use of GM crops may lower the use of some pesticides and herbicides, the use of the pesticide glyphosate has risen, and glyphosate was classified as "probably carcinogenic to humans" in 2015.

Environment

- Increased yields are listed as a main benefit of GM crops, but data has shown mixed evidence of increased yields.
- We have seen evidence of one unanticipated consequence already as nature responded to GM herbicide-tolerant crops with herbicide-resistant superweeds; the emergence of super-weeds increases pesticide use and decreases yields.
- One of the biggest purported benefits of GM crops, the ability to use no-till farming, is not exclusive to growing GM crops having been used for thousands of years in organic and conventional farming.
- GM crops that produce their own natural insecticide can negatively affect other insects.
- GM crops may have dire effects on biodiversity.
- GM crops are produced and sold by large corporations with poor environmental records that also sell herbicides and pesticides, such as glyphosate.

Business practices

- GM crops are more expensive due to patents and licensing.
- High prices lead to consolidation and more corporate factory farms as small farms drop out of the market, reducing farmer profits and increasing food costs for consumers.
- Costs for neighboring conventional or organic farms increase due to the burden of protecting conventional crops from irreversible genetic pollution from neighboring crops using GM technology.

Summary

- We can't know for sure what effect GM crops will have on the environment or our health, and after releasing them across the country it is too late to reverse course.

- Adding altered DNA from any organism outside a crop species is not natural. This process takes millions of years in nature, how can we know the consequences of making these changes overnight?

Positive information about GE

How does it work?

- Specific targeted changes to DNA are made within a crop.
- Since no new DNA is added to genetically edited crops, and similar gene changes could be achieved by conventional plant breeding no regulation is required for genetically edited crops to be grown.

Health and safety

- The US Department of Agriculture (USDA) has determined genetically edited food crops are safe for consumption and the environment since they do not contain new genetic material.
- The US Environmental Protection Agency (EPA) and the US Food and Drug Administration (FDA) regulate genetically edited food crops that are sent to them the same way they regulate conventional food crops.
- Genetically edited crops compared to conventional crops of the same variety show fewer toxins, carcinogens and allergens.
- Genetically edited crops are grown with less pesticide, herbicide and fertilizer than conventional crops.
- Genetic editing makes food healthier by enhancing nutrients and reducing toxins.

Environment:

- Genetically edited crops tolerate drought, frost, and other environmental stressors, making crop yields less uncertain.
- Genetically edited crops produce more food with less pesticides, feeding the world's growing population while decreasing the costs to health and the environment.
- Genetically edited crops that are herbicide-tolerant are grown with less synthetic insecticides using conservation tillage (less or no-till farming) which reduces greenhouse gases and increases soil health.
- The environmental and human health impact of synthetic pesticides can be dramatically lowered using genetically edited crops that produce their own natural pesticides.
- Genetically edited crops are grown using less fuel, reducing greenhouse gas emissions and can be used as renewable fuels and biodegradable plastic.
- Genetically edited crops can trap carbon capturing CO_2 emissions and increasing soil health.

Business Practices

- Genetically edited crops increase yield and profitability for farmers, ensuring food security, and lowering costs to consumers.
- Genetically edited crops are used by large and small farms equally providing economic opportunity for all.
- Genetically edited crops are regulated the same way as conventional crops, facilitating easier adoption by farmers and consumers.

- As genetically edited crops are increasingly used and accepted, growers and consumers will share in the economic benefits stimulating creation of even more beneficial crops to increase farm profits while protecting the environment and human health.

Summary

- The benefits of genetically edited crops could save the planet from climate change, make food healthier, and feed the world. Throwing out this technology could be throwing out a brighter future.
- Altering DNA through genetic editing removes the need to introduce DNA from other organisms, thus the USDA considers genetically edited crops conventional and not needing approval.

Negative information about GE

How does it work?

- Specific targeted changes are made within a crop.
- Since no new DNA is added to genetically edited crops, and similar gene changes could be achieved by conventional plant breeding no regulation is required for genetically edited crops to be grown.

Health and safety

- The US Department of Agriculture (USDA) has determined genetically edited (CRISPR) food crops are not required to go through the regulation process because they do not contain introduced genetic material.
- Genetically edited food crops do not go through any approval processes unless businesses volunteer to have their crops analyzed, so unhealthy changes that might occur may not be identified by a regulatory process.
- Even though no new genetic material is added, genetic editing can create unintentional issues like producing new allergens, toxins, or carcinogens in food through off-target effects.
- There may be unanticipated health effects that cannot be predicted or easily and quickly detected that thus are and will remain untested.
- While use of genetically edited crops may lower use of some pesticides and herbicides, use of the pesticide glyphosate has risen, and glyphosate was classified as "probably carcinogenic to humans" in 2015.

Environment

- Increased yields are listed as a main benefit of genetically edited products but data has shown mixed evidence of increased yields.
- We have seen evidence of unanticipated consequences with herbicide-resistant superweeds, which increases pesticide use and decreases yields.
- One of the biggest purported benefits of genetically edited crops, the ability to use no-till farming, is not exclusive to growing genetically edited crops having been used for thousands of years in organic and conventional farming.
- Genetically edited crops that produce their own natural insecticide can negatively affect other insects.
- Genetically edited crops may have dire effects on biodiversity.

- Genetically edited crops are produced and sold by large corporations with poor environmental records that also sell herbicides and pesticides, such as glyphosate.

Business practices

- Genetically edited crops are more expensive due to patents and licensing.
- High prices lead to consolidation and more corporate factory farms as small farms drop out of the market, reducing farmer profits, and increasing food costs for consumers.
- Costs for neighboring conventional or organic farms increase due to the burden of protecting conventional crops from irreversible genetic pollution from neighboring crops using genetic editing technology.

Summary

- Even though the USDA considers genetic editing safe since no DNA is added from outside the species, this process is not natural. DNA changes take millions of years in nature, how can we know the consequences of making these changes overnight?
- We can’t know for sure what effect genetically edited crops will have on the environment or our health, and after releasing them across the country it is too late to reverse course.