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Abstract

Foods with "clean labels," that is, foods with few ingredients, may mitigate the stigma from the lack of healthfulness in processed food products. However, with conventional technologies, clean labels are difficult to achieve. We conducted a survey, including choice experiment scenarios, in which half of the respondents were presented scenarios to purchase a shelf-stable ready meal with a clean label/fewer ingredients, and the other half were presented scenarios including the clean label/fewer ingredients and a new technology that allows for processed foods to be produced with fewer ingredients. In general, respondents were willing to pay a price premium for the clean label and the new food technology used. However, such preferences were heterogeneous. In the version of the survey that did not include the type of technology, the classes were "clean label incredulous," "moderate believers in clean labels," and "strong believers in clean labels." In the survey version including the type of technology, the classes were "clean label indifferent and technology takers," "moderate believers in clean labels and technology indifferent," and "strong believers in clean labels and technology indifferent." Our findings underscore the importance of providing consumers with information about a new technology and the resulting benefits to reduce perceived risks and increase consumer acceptance.

KEYWORDS

food technologies, labels, mixed logit, processed food products, willingness to pay

1 | INTRODUCTION

The decision of which foods to buy and consume is complex. In general, it is believed that individuals make rational choices guided by conscious motives, and explanations for their behavior can be explicitly studied and reported (Köster, 2003). Somewhat contrasting with this belief is that consumers do not process information in a systematic way, and that simple heuristics are used to select or eliminate products from a choice set, relying on a few salient quality characteristics (Combris et al., 2009). In this context, food labels constitute a powerful tool to communicate attributes of a food product and lead consumers to making informed choices. Food labels offer visual cues, and there is a plethora of information that can be included. Examples include, certification logos (e.g., organic certification, environmental sustainability, fair trade, locally grown, chemical free, and allergen free), production and expiration dates, how to best keep the food, net content, company ownership, ingredient list, and nutrition facts.

This study focuses on clean labels. In a broad sense, a clean label refers to the information in the ingredient list and is often characterized by being short, with simple claims familiar to the consumer, and indicating no artificial or chemical-sounding ingredients (Asioli et al., 2017). In a strict sense, there is no consensus on the definition of clean labels, and it is subject to consumers' interpretation and perception of the ingredients contained in the food product (Busken, 2013). Some practitioners claim that consumers' expectations of clean labels overlap with the idea of natural, organic, free from additives/preservatives, and less processed, as well as transparent information on the ingredients and practices of the processed food (Hartman Group, 2018; Ingredion, 2014). Others define a clean label as "no more than five ingredients or ingredients you cannot pronounce" (Pollan, 2008), while others mix the concept of "free of chemical additives" with "easy-to-understand list of ingredients" and "produced using traditional techniques with limited processing" (Edwards, 2013).

This article analyzes the consumers' perceptions of clean labels in presence of a new food technology. The dimension of the clean label as included in this study refers to a shorter list of ingredients, that is, fewer food additives and chemicals. As it relates to clean label, this study does not examine consumers' knowledge of food/chemical names. The inclusion of the new food technology hinges on the challenges faced by food-manufacturing companies to produce with existing food technologies wholesome foods that meet the ever-increasing demands for superior quality in terms of organoleptic and credence attributes including convenience and the nutritional quality of the ingredients. Innovative technologies are challenged to ensure production of a wholesome and simultaneously healthful/natural, optimal sensory quality, convenient, and affordable food product (Tang, 2015).

Part of the motivation for this study is to understand the consumer response to a new commercial-scale food-preservation technology based on microwave heating. The new technology is called Microwave Assisted Thermal Sterilization (MATS). For more information, please refer to Tang (2015). This technology is used to sterilize shelf-stable food products and also to pasteurize refrigerated prepared food products initially designed for ready meals. Sterilization consists of applying heat for a certain length of time at a corresponding temperature to kill pathogenic bacteria, ensuring food safety. The conventional thermal treatment applied to shelf-stable ready meals is "retort," where the product is sterilized and its shelf life at room temperature is prolonged for up to two years. These food products are found in the canned and packaged food section at grocery stores. However, depending on how the food handles the thermal treatment, it can adversely affect the taste, texture, and appearance.

MATS offers the potential for developing short-duration, in-package sterilization, using the same principles as a microwave oven. This technology allows companies to sterilize food products in a way that retains their organoleptic qualities, making them more similar to a recently prepared meal. This technology also enables using fewer ingredients, which usually means using less food preservatives compared to the current sterilization practices, making it possible to have an end product with a clean label.

As clean labels become more popular with consumers, a technology that preserves foods without the inclusion of a long list of additives or preservatives will also become more valuable to food manufacturers. However,

consumers often mistrust and are hesitant to accept new food technologies, in most cases, delaying new technology adoption by food manufacturers (Berwald et al., 2006; Cardello, 2003; Cox & Evans, 2008; Ronteltap et al., 2007; Ueland et al., 2012). Given that existing status quo technologies are not always conducive to produce food products that would meet all the ever-increasing consumers' demands, further research is warranted to better understand consumers' reactions towards new food technologies that would enable producing, in a more efficient manner, the food products with the attributes most desired by consumers.

The objective of this study is to analyze the possible heterogeneity across consumers in their willingness to pay (WTP) for clean labels/fewer ingredients in a shelf-stable ready meal, with and without including the food technology used as an additional attribute. The term "clean label" in this manuscript refers only to the shorter list of ingredients, that is, fewer food additives and chemicals included in the ready meal. A latent class segmentation was conducted to investigate the presence of consumer segments that are more responsive to clean labels and to new food technologies than other segments. The main contribution of this study is to advance the understanding of consumers' preferences for foods with fewer ingredients in the presence of a new food technology.

2 | LITERATURE REVIEW

Few studies have analyzed consumers' perceptions of clean labels. Only the study by Asioli et al. (2017) focused on clean labels and suggested that psychological, biological and physiological, intrinsic product characteristics, extrinsic product characteristics, situational and sociocultural factors, and price are factors impacting consumers' preferences for clean labels. They concluded that the notion of "free from" or "natural" is the most important factor driving consumers' preference for clean labels. That is, "health," whether that is the health claims, healthiness of a product, or a consumer's health concerns was the main consumer motivation to prefer a clean label.

Contrastingly, abundant literature has focused on health-related labels in food products, not necessarily involving a clean label (Román et al., 2017; Rozin et al., 2004, 2012). Studies centered around the estimation of WTP for organic processed foods, processed foods free of chemicals, or ingredients developed via genetic modification (GM or GMO) have found that price premiums stem from the notion that organic is related to chemical free or GMO free (Batte et al., 2007; Peterson & Li, 2011). A handful of studies found that consumers with greater health concerns are more likely to consume products with organic and GMO-free ingredients in processed foods (Asif et al., 2018; Basha et al., 2015; Ditlevsen et al., 2019; Hartmann et al., 2018).

Several studies have shown that naturalness of food products is of great importance to consumers and is often associated with healthiness (Abouab & Gomez, 2015; Bredahl, 1999; Dickson-Spillmann et al., 2011; Evans de Challemaison & Cox, 2010; Moscato & Machin, 2018; Rozin et al., 2004). Also, studies have linked established food technologies, such as pasteurization, with a decreased perception of the production's naturalness (Abouab & Gomez, 2015; Rozin et al., 2004).

A different branch of literature suggests that nowadays consumers show interest in knowing more about the technologies used to produce and prepare the food they consume (Brunner et al., 2018; Dickson-Spillmann et al., 2011; Hwang et al., 2005; Kiesel et al., 2005). Along with the increased interest are also the increased concerns toward new food technologies (Brunner et al., 2018; Cardello, 2003; Cox & Evans, 2008; Ronteltap et al., 2007; Ueland et al., 2012). Among new food technologies, greater concerns are shown for genetic modification compared to others like pasteurization, use of artificial colors, and use of food preservatives (Hwang et al., 2005). The present study focuses on MATS. Microwave technology itself is not new, as it has been used as a safe means for heating and cooking food. In fact, in 1992 alone, an estimated 92% of households in the United States had a microwave oven (Giese, 1992). Given that processed foods are already associated with a certain degree of unnaturalness, findings in this study will provide evidence that an alternative food technology may be more readily accepted if the ingredient list is shorter, suggesting that fewer food additives or preservatives were used.

3 | METHODOLOGY

3.1 | Experimental design and data collection

The present study utilized an online survey platform, Qualtrics, along with the Qualtrics market research consumer panel to recruit a representative sample of consumers across the United States. The randomly selected sample of U.S. consumers follows the U.S. Census demographics in terms of age, income, and rural/urban residence. In addition, the selection criteria included that the individuals must be responsible for their households' grocery shopping and must have consumed a shelf-stable ready meal at least once in the last month. The reason for screening for individuals who have consumed a ready meal at least once in the last month, is to mitigate hypothetical bias, ensuring that respondents are familiar with the product being analyzed (List & Gallet, 2001). In general, ready meal consumption is not widespread across consumers. Zhang and Gallardo (2018) found that, on average, from 2008 to 2016, only 3.44% of all households included in a grocery store scanner data set have purchased ready meals at least once.

A between-subjects design was used to randomly group the sample of respondents in two groups. Each group received one of two versions of the survey. One group received the survey version in which the discrete choice experiment included, as an attribute, the name of the food technology, that is, the new food technology versus the conventional technology, along with the clean label/fewer ingredients attribute. The other group received the survey version in which the discrete choice experiment did not include the name of the food technology as an attribute—that is, this version included only the clean label/fewer ingredients attribute. Between the two versions there were 349 and 350 completed surveys collected, respectively. The survey was administered from September 13, 2017, through October 1, 2017. In addition to the discrete choice experiment, the survey included questions about grocery store shopping habits, food consumption habits in general, and food consumption habits focusing on ready meals. Further, the survey included questions about attitudes towards microwave technology and the importance of labels in one's food-purchase decisions. Finally, sociodemographic questions were asked.

A shelf-stable macaroni-and-cheese meal was the food used in the choice experiments. In each discrete choice scenario, respondents were presented with a hypothetical situation in which they had to choose to buy the food product between two alternatives. Each alternative presented a random combination of the length of the label, that is, the number of ingredients and the price. In the alternative survey version, respondents were presented with the same choice scenario, with the addition of the name of the technology used for sterilization, that is, MATS or retort. In the latter case, before the respondents were presented the scenarios, they were provided with information about each technology, as presented in Figure 1. In both survey versions, respondents were also given a “no-buy” option, meaning they would not purchase either food product.

The random combination of the attributes in each scenario originated from a fractional factorial design generated using JMP software. JMP uses a two-step procedure, using an algorithm based on Kessels et al. (2011). First, we determined the constant attributes and their levels (i.e., determined which attributes to hold identical for all alternatives; the set of constant attributes changes in each choice scenario). Second, we selected levels for the remaining, varying attributes to maximize D-efficiency.

The fractional factorial designed minimized the number of scenarios, mitigating potential respondent fatigue while maximizing D-G-A efficiencies. The first version without information about the food technology used is based on a $2^2 \times 2^3$ design, that would have initially yielded 32 scenarios; with the fractional factorial, the design ended with 8 scenarios. The design maximized the D-efficiency value at 98%. The second version that included information about the food technology is based on a $2^2 \times 2^2 \times 2^3$ design that would have initially yielded 128 scenarios; with the fractional factorial the design ended with 8 scenarios. Similarly, the design maximized the D- efficiency with values at 99%.

The list of the ingredients used in the clean label/shorter list is from a macaroni-and-cheese ready meal cooked and preserved using the new food technology in consultation with food scientists with expertise in MATS

	Option A	Option B	Option C
Label - Ingredients	 **Ingredients** **Water, Enriched Macaroni** (Semolina [Wheat], Water, Egg White, Niacin, Ferrous Sulfate [Iron], Thiamin Mononitrate, Riboflavin, Folic Acid), **Pasteurized Process Swiss and American Cheese** (Cultured Milk and Skim Milk, Cream, Sodium Phosphate, Salt, Sorbic Acid [Preservative], Enzymes), **Pasteurized Process American Cheese** (Milk, Salt, Cheese Cultures, Enzymes, Water, Sodium Phosphate, Cream, Salt, Lactic Acid), **Milk (Contains Vitamin D3),** Contains 2% or less of Canola Oil, Modified Cornstarch (Contains Erythorbic Acid), Parmesan Cheese (Pasteurized Part-Skim Milk, Cheese Cultures, Salt, Enzymes, Powdered Cellulose to Prevent Caking, Sorbic Acid to Protect Flavor), Cream Cheese (Pasteurized Milk and Cream, Cheese Cultures, Salt, Carob Bean Gum), Potato Starch, Potassium Chloride, Yeast Extract (contains Maltodextrin), Soy Protein Concentrate, Onion Powder, Rice Flour, Carotene Color (Carotene, Sucrose esters, Ascorbyl palmitate, and DL alpha tocopherol), Annatto Color.	 **Ingredients** **Water, Enriched Elbow Macaroni** [semolina (wheat), egg whites, niacin, ferrous sulfate, thiamin mononitrate, riboflavin, and folic acid], **Cheddar Cheese** [milk, cheese culture, salt, enzymes], Contains 2% or less of butter, modified food starch, salt, sugar, disodium phosphate.	Neither option
Technology	Retort	MATS	
Price	$0.99 /15 oz. serves 2	$2.99 /15 oz. serves 2	
I would choose			

FIGURE 1 Example of a discrete choice scenario used in the survey version in which the information about the new food technology was included. In this question, you will be given scenarios that mimic a grocery shopping experience for shelf-stable, ready-to-eat meals. Each scenario will consist of two options, each containing the same ready-to-eat meal randomly assigned option A or B, differing in the list of ingredients, the technology used, and the price. In each scenario, please select **ONE** option you would be willing to buy. You can always choose none of the options presented, option C. *Processing technologies*: Shelf-stable, ready-to-eat meals found in the canned/packaged food section at grocery stores are sterilized for food safety. Many of the foods we eat have been sterilized, such as canned soup or salmon pouches. Food that has been sterilized is heated up to a certain temperature and length of time to kill off bacteria. Consider a new processing technology that allows meals to be produced with fewer ingredients while improving the food's quality. *Retort*: This is the traditional thermal treatment applied to ready-to-eat processed food products. This is the CURRENT technology used for most shelf-stable, ready-to-eat foods. Typically, it is performed under pressure in pressure cookers, called retorts. The product is sterilized and its shelf life without refrigeration is prolonged, for example, up to 2 years. However, food generally does not preserve its original quality characteristics. *Microwave sterilization*: MATS is an effective means to deliver energy to food through polymeric package materials, offering the potential for developing short-time in-package sterilization processes. This is the SAME principle used for the microwave oven you have at home. Food prepared using MATS have quality characteristics close to those prepared at homes or in restaurants. Also, foods prepared with MATS require minimal processing, allowing food products to be made with fewer ingredients than traditional sterilized foods. *No food preservatives are needed for both methods.* MATS, Microwave Assisted Thermal Sterilization [Color figure can be viewed at wileyonlinelibrary.com]

technology. This study uses a shelf-stable macaroni and cheese, because this product was used to test the first commercial-scale prototypes of MATS. The list to be used for the label with more ingredients came from a macaroni-and-cheese ready meal that was available in the market at the time of the experiment. The label attribute was coded as a binary variable where 1 represented the "clean label" with fewer ingredients. The choice of technology types came from our desire to examine the WTP for the new technology. Retort technology is the most common food sterilization method used in the industry. The technology attribute was coded as a binary variable where 1 represented the new technology. The range of prices was chosen based on current market prices for shelf-stable, ready macaroni and cheese. Price was coded as \$0.99, \$1.99, and \$2.99 per 15 oz serving size (15 oz = 425 g). These prices were consistent with contemporaneous grocery store prices for shelf-stable macaroni cheese.

3.2 | Empirical specification

The theoretical basis for our empirical approach rests on Lancaster's (1966) theory of demand for characteristics. Consumers derive utility from a function of attributes inherent to the good rather than the good itself. Also, this study follows the random utility theory that assumes the utility derived by a consumer, is composed of a deterministic component given by the goods attributes and a random component given by unobserved factors (McFadden, 1974). According to the random utility theory, a consumer receives utility from choosing one alternative from a finite set of alternatives in a choice set, if, and only if, this alternative provides at least as much utility as any other alternative.

Specifically, the empirical setting follows the mixed logit specification where consumer n's utility U from choosing alternative i among a set of j alternatives in the choice set M, in each of the t choice scenarios (t = 1,2, …, T) follows,

$$U_{jnit} = \alpha_j + \beta_n x_{nit} + \gamma p_{it} + \varepsilon_{nit}, \tag{1}$$

where α_j denotes the alternative specific constant (ASC) that captures the opt-out option, the vector x_{nit} denotes m observed attributes of choice (clean label/fewer ingredients, and name of the food technology used), p_{it} denotes price; β_n is an unobserved random coefficient vector for each n, assumed to follow a normal distribution with density $f(\beta_n \mid \theta)$, where θ is the true parameter of the distribution; γ is the coefficient estimate for price assumed fixed; and ε_{nit} is an unobserved error term that is assumed to be identically and independently distributed.

Conditional on β_n, the probability consumer n chooses alternative i in choice scenario t is,

$$Pr_{nit} = L_{nit}(\beta_n) = \frac{\exp(\beta_n x_{nit})}{\sum_{j=1}^{M} \exp(\beta_n x_{njt})}. \tag{2}$$

The unconditional probability of choosing a specific alternative is the integral of the conditional probability over all possible values of β and is given by,

$$Pr_{nit}(\theta) = \int Pr_{nit} f(\beta_n \mid \theta) d\beta_n. \tag{3}$$

The probability of each consumer n making a sequence of choices is,

$$Pr_n = \prod_{t=1}^{T} \prod_{i=1}^{M} \left(\frac{\exp(\beta_n x_{nit})}{\sum_{j=1}^{M} \exp(\beta_n x_{njt})} \right)^{y_{nit}}, \tag{4}$$

where y_{nit} denotes an indicator function that is 1 if consumer n chooses alternative i in choice scenario t, and 0 otherwise (Train, 2009). The parameter estimates are computed by maximum likelihood estimation in STATA.

To infer the presence of consumer segments, this study uses a latent class model following Ikiz et al. (2018). According to the latent class model, consumers' preferences differ across classes but remain homogeneous within a

class. The probability that consumer n chooses alternative i in choice scenario t, given that she is assigned to latent class c, is,

$$Pr\ (nit|c) = \frac{exp\ (\beta_c x_{nit})}{\sum_{j=1}^{M} exp\ (\beta_c x_{njt})}, i \neq j. \tag{5}$$

For class assignment c, the probability of consumer n making a sequence of choices is the joint probability,

$$Pr_n(c) = \prod_{t=1}^{T}\prod_{i=1}^{M}\left(\frac{\exp\ (\beta_c x_{nit})}{\sum_{j=1}^{M}\exp\ (\beta_c x_{njt})}\right)^{y_{nit}}, i \neq j, \tag{6}$$

where y_{nit} denotes an indicator function that is 1 if consumer n chooses alternative i in choice scenario t, and 0 otherwise. Since class membership status is not observable, the probability that consumer n is assigned to class c is specified as,

$$Pr_{nc}(\delta) = \frac{\exp\ (\delta_c z_n)}{1 + \sum_{k=1}^{C-1}\exp\ (\delta_k z_n)}, c \neq k, \tag{7}$$

where z_n is a set of observable characteristics for consumer n and $\delta = (\delta_1, \delta_2, ..., \delta_{C-1})$ is a vector of membership parameters. For normalization, membership parameters for one of the classes are fixed to zero.

Typically, the criteria used to select the optimal number of classes consist of analyzing the measures of goodness of fit: Akaike Information Criterion (AIC), Consistent Akaike Information Criterion (CAIC), and the Bayesian Information Criterion (BIC). Following these measures of goodness of fit, we opt for the models with three classes in both survey versions (Table 1). The models with three classes exhibit the third to the lowest values for AIC, CAIC, and BIC and the highest values for prediction accuracy. The model with four and five classes exhibits the lowest values for AIC, CAIC, and BIC but not the highest prediction accuracy. Additional criteria used to select three classes include the fact that consistently across both survey versions a larger number of membership class variables are statistically significative compared to the model with four classes. This indicates that the model with three classes is better separated than the model with four (Nylund-Gibson & Choi, 2018). Further, past research

TABLE 1 Model selection for latent class logit model using measures of goodness of fit

Classes	LLF[a]	Number of parameters	AIC[b]	CAIC[c]	BIC[d]	Posterior prediction accuracy
Not including the name of the food technology used						
2	−2031.46	21	4104.92	4206.93	4185.93	0.98
3	−1759.87	39	3597.73	3787.19	3748.19	0.98
4	−1630.27	57	3374.53	3651.43	3594.43	0.97
5	−1570.03	75	3290.05	3654.40	3579.40	0.97
Including the name of the food technology used						
2	−2125.82	21	4293.63	4395.59	4374.59	0.94
3	−1969.85	39	4017.70	4207.05	4168.05	0.96
4	−1773.72	57	3661.45	3938.19	3881.19	0.72
5	−1740.15	75	3630.30	3994.43	3919.43	0.95

[a]LLF means log likelihood function.

[b]AIC means Akaike Information Criterion.

[c]BIC means Bayesian Information Criterion.

[d]CAIC means Consistent Akaike Information Criterion.

supports the statistical significance, interpretability of parameter estimates, and sample size as more powerful criteria to select the number of classes in a latent class model (Greene & Hensher, 2003; Pacifico & Yoo, 2012).

The latent class model includes a vector of individual-specific characteristics that are described by a membership function. In this study, the class membership function includes sociodemographic variables: millennial is a binary variable equaling 1 if the respondent was born in and after 1982. Income is a binary variable equaling 1 if the respondent earned more than $67,000 in 2017, which is the average income reported by all respondents to both versions of the survey. White ethnicity is a binary variable equaling 1 if the respondent belonged to the white ethnicity. The number of people in the household was a binary variable equaling 1 if the number of people in the household is two or more. The number of children under 18 years old was a binary variable equaling 1 if there are two or more children under 18 years old in the household. Large city is a binary variable equaling 1 if the respondent chose living in a large city as the place of residence. Self-perceived healthy is a binary variable equaling 1 if respondents considered their health status as somewhat healthy and healthy. The rate of importance of labels was also included in the membership function. Low sodium content is a binary variable that equals 1 if the respondents rated low sodium as important or extremely important in a 1–7 point scale (1 = extremely unimportant, 7 = extremely important). Similarly, absence of artificial ingredients, contains phytonutrients (e.g., vitamins, antioxidants), gluten free, low carbohydrates, heart healthy, and low cholesterol are binary variables that equal 1 if the respondents rated as important or extremely important each of the mentioned messages in the food label.

4 | RESULTS AND DISCUSSION

4.1 | Respondents' sociodemographic profile

Table 2 presents the summary statistics of the sociodemographic profile of the two samples of respondents: the sample responding to the survey version that includes the food technology used as an attribute of the discrete choice experiment and the sample responding to the survey that does not include the food technology used. Both samples of respondents are similar in proportion of females, community of residence, employment, income, region of the United States, number of people in the household, number of children under 18 years old, perceived health status, and activity level. Differences are observed for education attained and age. The group of respondents for the survey version omitting the information on the food technology used includes a higher proportion of respondents who completed more than four years of college. This same group is, on average, 54 years old, older compared to the other group of respondents whose average age is 51 years old. Considering this disparity in education levels between respondents to each survey version, we use weighted data in both the mixed logit and latent class models. Data from the survey version that does not include information on the food technology were weighted by the proportion of individuals who attained a four-year college degree and beyond (ratio = 1.16). That is, all observations from the survey version not including the type of technology were divided by 1.16 to correct for over-representation, following the weighting procedure in Lusk et al. (2003).

When compared to the 2017 U.S. Census, our sample represents more women who are more educated, older, and wealthier, and more respondents of white ethnicity when compared to the general U.S. population. Our survey respondents' profiles follow the profile of individuals who tend to be more responsive to surveys (Curtin et al., 2000). Urban/rural, employment, and regional distribution of respondents of our survey is comparable to the general U.S. Census Bureau (2016, 2017a, 2017b, 2017c, 2017d, 2017e, 2017f). In relation to shopping habits, 48% on average shop for two people, and 74% do not shop for anyone under the age of 18. As for self-perceived health, 44% of respondents reported themselves as somewhat healthy and 29% as healthy. Also, 42% reported being somewhat active and 33% active.

TABLE 2 Summary statistics of sociodemographics by survey compared to the U.S. Census

Variable	Description	Sample not including the name of the food technology	Sample including the name of the food technology	T test comparison between samples	U.S. Census 2017
Gender	1 if male	23.14	25.50	0.73	48.69
	2 if female	76.86	74.50		51.31
Education	1 if some school	0.57	1.15		12.10[a]
	2 if high school graduate	18.00	21.78		27.69
	3 if community college	20.00	24.07		30.80
	4 if 4-year college or university	34.29	35.53		18.63
	5 if advanced or professional degree	27.14	17.48		10.78
	>4 years college	61.43	53.01	2.25*,***	
Community	1 if rural area	20.00	19.77	0.23	19.30[b]
	2 if small town	29.71	29.51		80.70
	3 if small city	26.86	26.07		
	4 if large city	23.43	24.64		
Employment	1 Manual labor	4.86	10.37	0.31	
	2 Services and hospitality	10.57	9.51		
	3 Educ., business, and information	38.29	31.99		
	4 Miscellaneous	2.86	3.46		
	5 Retired	11.14	9.46		
	6 Not employed	32.29	34.96		
Age	1 if 24 years or less	0.57	3.44		12.23
	2 if 25-34 years	17.14	21.20		17.84
	3 if 35-44 years	11.43	14.61		16.31
	4 if 45-54 years	12.86	13.18		16.79
	5 if 55-64 years	26.57	20.63		16.67
	6 if 65+ years	31.43	26.93		20.16
	Average age	54.06	50.77	2.73**	
Income	1 <$25,000/year	7.14	10.32	1.53	20.30
	2 if $25,000–$34,999/year	10.00	11.17		9.10
	3 if $35,000–$49,999/year	15.43	13.47		12.70
	4 if $50,000–$74,999/year	21.14	23.78		17.60
	5 if $75,000–$99,999/year	17.71	16.33		12.50
	6 if $100,000/year or more	28.57	24.93		27.80

TABLE 2 (Continued)

Variable	Description	Sample not including the name of the food technology	Sample including the name of the food technology	T test comparison between samples	U.S. Census 2017
Race	1 if Amer Indian or Alaskan Native	0.86	0.57		0.66
	2 if Asian, Asian American	3.14	4.87		5.53
	3 if Black	2.29	4.01		12.32
	4 if Hispanic, Latino American	2.29	4.87		18.07
	5 if Middle Eastern	0.57	-		0.26
	6 if Pacific Islander	-	-		0.17
	7 if White	87.71	84.81	1.11	60.57
	8 if Mixed race	1.43	0.86		2.44
	9 if Prefer not to respond	1.71	-		
Region	1 if New England	5.71	7.16	1.62	4.71
	2 if Middle Atlantic	20.29	9.46		13.05
	3 if East North Central	16.86	20.63		14.46
	4 if West North Central	9.71	8.60		6.47
	5 if South Atlantic	15.43	19.77		20.00
	6 if East South Central	6.29	6.02		5.82
	7 if West South Central	6.57	8.02		11.82
	8 if Mountain	10.86	8.88		7.30
	9 if Pacific	8.29	11.17		16.36
	10 if Other	-	0.29		
No. of people in the household	1 if one person	22.86	21.20	0.79	
	2 if two people	48.57	48.14		
	3 if three people	14.00	14.04		
	4 if four or more people	14.57	16.6		
No. of people in the household under 18	1 if no one	75.43	73.35	0.93	
	2 if one person	11.71	12.32		
	3 if two people	9.14	9.46		
	4 if three people	3.43	3.15		
	5 if four or more people	0.29	1.72		
Health status	1 if not healthy	3.43	1.15	0.86	
	2 if somewhat healthy	8.00	12.03		
	3 if neither healthy nor unhealthy	12.86	16.33		
	4 if somewhat healthy	45.43	42.12		
	5 if healthy	30.29	28.37		

(Continues)

TABLE 2 (Continued)

Variable	Description	Sample not including the name of the food technology	Sample including the name of the food technology	T test comparison between samples	U.S. Census 2017
Activity level	1 if not active, never exercise	9.71	10.89	0.20	
	2 if somewhat active	43.71	40.11		
	3 if active, exercise 1-3 times/week	31.71	34.10		
	4 if very active, exercise >4/week	14.86	14.90		

Note: Results from a two-sided *t* test where the null hypothesis is that the difference between the means of the two samples is zero for a given variable using a 95% confidence interval.

*, **, and ***denote significance at the 10%, 5%, and 1% level respectively.

[a]The U.S. census data groups did not match perfectly with the surveys but were adjusted to be closer.

[b]These are based on 2016 estimates.

[c]There was no direct group for those of Middle Eastern descent in the Census, so it is in comparison to the "other" category.

4.2 | Impact of clean labels and new technology on consumers' utility

Parameter estimates for the mixed logit estimations are presented in Table 3. In both samples, with and without the inclusion of the name of the food technology used, the coefficient for the price is negative and significant, which is consistent with the law of demand. The estimated coefficient for clean label/fewer ingredients is positive and significant in both samples, suggesting that, if given the option of fewer ingredients, the respondent's average marginal utility for that option rises, compared to a label with more ingredients. When comparing the coefficient estimates obtained from the two different survey versions, the coefficient estimates corresponding to price and clean label are larger in magnitude for the survey version not including the name of the food technology used.

When including the name of the food technology used, the coefficient estimate is positive, suggesting that respondents were more likely to choose the new technology over the conventional retort technology for shelf-stable products. This finding should be contrasted with previous studies on new food technologies. The fact that the new technology uses the familiar term "microwave" may be driving this result. Microwave technology itself is not new, as it has long been used as a safe means for heating and cooking food (Giese, 1992). The ASC for the opt out option in both survey versions is negative and statistically significant, indicating that respondents in general prefer one of the alternative scenarios presented over the opt out option. The standard deviation of the attributes in both survey versions are statistically significant, suggesting that there was heterogeneity in preferences for the clean labels and food technologies used.

WTP estimates are presented in Table 4. The sample of consumers who responded to the choice experiment that did not include the name of the food technology used have an estimated mean WTP premium of $1.19/15 oz unit ($1.19/425 g unit) for macaroni and cheese with fewer ingredients. Whereas the sample of consumers who responded to the choice experiment that included the name of the food technology used have an estimated mean WTP premium of $1.58/15 oz unit ($1.58/425 g unit) for the macaroni and cheese with fewer ingredients, and a premium of $0.16/15 oz ($0.16/425 g unit) for the new food technology MATS compared to retort. Comparing the WTP between each survey version, respondents who received the survey version including the name of the technology used stated a higher WTP for clean labels compared to those who received the version without the name of the technology used. The difference is statistically significant at the 99% level.

TABLE 3 Parameter estimates for the mixed logit model to depict consumers' preferences for clean labels and food technology

Variables	Parameter estimates: Not including the attribute name of the food technology	Parameter estimates: Including the attribute name of the food technology	*T* test comparison
	Means		
Price	−1.23*** (0.09)	−0.74*** (0.04)	
Clean label/fewer ingredients	1.46*** (0.19)	1.16*** (0.12)	1.96**
New food technology	-	0.12** (0.07)	
Alternative specific constant—no option	−2.37*** (0.15)	−2.14*** (0.10)	
	SD		
Clean label/fewer ingredients	2.60*** (0.16)	1.74*** (0.12)	
New food technology	-	0.76*** (0.08)	
Number of respondents	350	349	
Log-likelihood	−2041.24	−2252.80	

Note: *SEs* in parentheses.

** and *** denote significance at the 5% and 1% level respectively.

4.3 | Profiling consumer segments

Table 5 presents the results of the latent class models. Columns 2, 3, and 4 of Table 5 present the results of the survey version without including the name of the food technology used. Based on the coefficient estimates, three classes were identified: “clean label incredulous,” or class 1, the “moderate believers in clean labels,” or class 2, and “strong believers in clean labels,” or class 3. These classes follow the coefficient estimates for clean label. The “clean label incredulous” group exhibited a negative and statistically significant coefficient estimate for clean

TABLE 4 Willingness to pay estimates for “clean label” and technology by model specification

	Willingness to pay estimates ($/15 oz unit[a] of shelf-stable macaroni and cheese): Not including the food technology attribute	Willingness to pay estimates ($/15 oz unit[a] of shelf-stable macaroni and cheese): Including the food technology attribute	*T* test comparison
Clean label/fewer ingredients	1.19 [0.90, 1.45][b]	1.58 [1.24, 1.90]	−2.75***
New food technology	–	0.16 [−0.01, 0.32]	

Note: 95% confidence intervals in brackets.

***Significant at the 1% level.

[a]15 oz = 425 g.

[b]95% confidence interval.

label/shorter list of ingredients. The “moderate believers in clean labels” exhibit a positive coefficient estimate but not as large in magnitude (0.83) as the “strong believers in clean labels” (5.00). Thirty-nine percent of respondents fall into class 1, 21% into class 2, and 40% into class 3. In all three classes, the parameter estimate for price was negative and significant, following the law of demand. The “strong believers in clean labels” class was more responsive to price (−1.60) compared to the “clean label incredulous” and “moderate believers in clean labels” classes (−1.38 and −0.43, respectively). The “strong believers in clean labels” exhibited the highest marginal utility from a clean label (5.00) compared to the “moderate believers in clean labels” (0.83) and the “clean label incredulous” (−0.47). The “moderate believers in clean labels” were more likely to choose the option not to buy (1.19) compared to the “clean label incredulous” (−5.32) and “strong believers in clean labels” (−1.13).

The class membership coefficient estimates are presented in Table 5. The class “strong believers in clean labels” are used as the base for comparison. The class “strong believers in clean labels” compared to the “moderate believers in clean labels” had a lower proportion of millennials, a greater proportion of individuals of white ethnicity, a lesser proportion of individuals for whom the message of low-sodium content in a label is important, and greater proportion of individuals for whom a label indicating low-carbohydrate content is important. Contrastingly, the class “strong believers in clean labels” compared to the “clean label incredulous” had a greater proportion of individuals with an annual income higher than $67,000, a smaller proportion of households with children younger than 18 years old, perceived themselves as healthier, considered the message absence of artificial ingredients in the labels more important, and considered the message gluten free in labels less important.

Columns 5, 6, and 7 of Table 5 present the results from the latent class model for the survey, including the name of the food technology used. We used the same variables in the membership function across versions of the survey; however, different classes were found. The differences in classes between each survey version are due to the different coefficient estimates obtained for each class as the variable for information on food technology used is included in this model. In this version, 56% of respondents were “clean label indifferent and technology takers.” For this group, the coefficient estimate for the clean label is not statistically significant, whereas the coefficient estimate for the new food technology variable is positive and statistically significant (0.15). Thirteen percent of the respondents to this survey version were “moderate believers in clean labels and technology indifferent.” This group exhibits a positive and statistically significant coefficient estimate for clean label variable (1.79), while the coefficient estimate for the information on the new food technology is not statistically significant. Thirty-one percent of the respondents were “strong believers in clean labels and technology indifferent.” This group exhibits a coefficient estimate for clean labels that is positive, statistically significant, and larger in magnitude than the coefficient estimate for the “moderate believers in clean labels and technology indifferent” group, whereas the coefficient estimate for the information on the new food technology is not statistically significant. On the coefficient estimate for price, the “strong believers in clean labels and technology indifferent” class was more responsive to price (−0.81) compared to the “clean label indifferent and technology takers” class (−0.74). The class “clean label indifferent and technology takers” exhibited a non-statistically significant parameter estimate for price.

The class membership for the coefficient estimates for the survey version including the food technology used are also presented in Table 5. The “strong believers in clean labels and technology indifferent” compared to the “moderate believers in clean labels and technology indifferent” exhibit a larger proportion of individuals with an annual income higher than $67,000, smaller proportion of individuals with children <18 years in the household, and a larger proportion of individuals for whom a label indicating the absence of artificial ingredients is important. There were no statistically significant differences in the class membership parameter estimates between the strong believers in clean labels and technology indifferent and the clean label indifferent and technology takers.

TABLE 5 Parameter estimates for latent class logit and membership functions by survey version

	Not including the food technology attribute			Including the food technology attribute		
	Clean label incredulous (1)	Moderate believers in clean labels (2)	Strong believers in clean labels (3)	Clean label indifferent and technology takers (2)	Moderate believers in clean labels and technology indifferent (3)	Strong believers in clean labels and technology indifferent (1)
Price	−1.38***	−0.43***	−1.60***	−0.74***	−0.22	−0.81***
	(0.09)	(0.13)	(0.19)	(0.05)	(0.05)	(0.12)
Clean label/fewer ingredients	−0.47**	0.83***	5.00***	−0.10	1.79***	4.41***
	(0.11)	(0.20)	(0.40)	(0.08)	(0.42)	(0.30)
New food technology	-	-	-	0.15**	−0.04	−0.24
				(0.06)	(0.20)	(0.19)
Alt. spec. const.–None option	−5.32***	1.19***	−1.13***	−4.11***	1.87***	−0.78***
	(0.27)	(0.25)	(0.38)	(0.24)	(0.39)	(0.29)
Log-likelihood	−1759.9	−1759.9	−1759.9	−1773.3	−1773.3	−1773.3
Class membership estimates						
Class share	39%	21%	40%	56%	13%	31%
Millennial	0.30	0.78*	-	0.46	-	0.42
	(0.37)	(0.41)		(0.46)		(0.52)
Income > $67,7000/year	−0.77**	0.09	-	0.56	-	0.79*
	(0.29)	(0.34)		(0.40)		(0.44)
White	−0.30	−0.90*	-	0.14	-	0.30
	(0.45)	(0.48)		(0.50)		(0.57)
Number of people in household	0.33	0.47	-	−0.34	-	−0.02
	(0.34)	(0.43)		(0.50)		(0.55)
Number of children in household	0.61*	−0.44	-	−0.26	-	−1.11**
	(0.35)	(0.44)		(0.42)		(0.49)
If lives in large city	0.09	0.10	-	−0.28	-	−0.03
	(0.33)	(0.39)		(0.43)		(0.48)
Self-perceived healthy	−0.68**	−0.23	-	0.22	-	0.55
	(0.33)	(0.43)		(0.40)		(0.46)
Importance of labels						
Low sodium content	0.57	0.93**	-	−0.27	-	−0.36
	(0.37)	(0.43)		(0.42)		(0.47)
Absence of artificial ingredients	−0.73**	0.25	-	−0.33	-	0.87*
	(0.33)	(0.38)		(0.47)		(0.50)

(Continues)

TABLE 5 (Continued)

	Not including the food technology attribute			Including the food technology attribute		
	Clean label incredulous (1)	Moderate believers in clean labels (2)	Strong believers in clean labels (3)	Clean label indifferent and technology takers (2)	Moderate believers in clean labels and technology indifferent (3)	Strong believers in clean labels and technology indifferent (1)
Contains phytonutrients (vitamins, antioxidants)	−0.28	0.47	-	1.37	-	0.19
	(0.42)	(0.45)		(0.56)		(0.60)
Gluten free	1.04*	0.91	-	−0.13	-	−1.20
	(0.59)	(0.65)		(0.56)		(0.73)
Low carbohydrates	−0.47	−1.30***	-	−0.31	-	−0.36
	(0.39)	(0.50)		(0.47)		(0.52)
Heart healthy	0.23	−0.05	-	−0.35	-	−0.01
	(0.38)	(0.50)		(0.58)		(0.61)
Low cholesterol	−0.22	0.06	-	0.12	-	0.06
	(0.58)	(0.54)		(0.63)		(0.67)

Note: *SE*s in parentheses.

*, **, and *** denote significance at the 10%, 5%, and 1% level respectively.

4.4 | Overall discussion

Overall, our study suggests that providing products with clean labels/fewer ingredients has the potential to command a premium for such products, although this preference for clean labels/fewer ingredients is not homogeneous across survey respondents. In fact, 39% of respondents to the survey version not including the name of food technology used indicated a negative marginal utility for clean labels. This group is the one that exhibits a larger proportion of individuals with lower than a $67,000 annual income, have children in the household, and are self-perceived as less healthy. This group does not consider the message “absence of artificial ingredients” as important in the labels but does consider a gluten free label as more important.

A challenge is to produce processed foods that meet the clean label criteria. Technological breakthroughs can successfully meet this challenge. Because consumers are often wary of new technologies, especially when it comes to the food they eat, it is important to consider the consumer's perception of the benefits accrued when accepting the new technology. In this study, it is a processed food with cleaner labels/fewer ingredients. Another consideration is the name or the type of the new technology and the product to which it is applied. In this study, the new technology is based on and named after a massively adopted technology. The fact that the new technology uses the familiar term “microwave” is likely a factor that increases its acceptance by consumers. In fact, 56% of respondents in the survey version that included information on the type of technology exhibited a positive marginal utility for the new food technology.

It is important to note, though, that consumers should be informed about the food technologies used, to reduce information asymmetries and potential food technology neophobias. If left unexplained, products processed via new technology may be perceived as risky due to consumers' unfamiliarity and might be rejected much like other food technologies that are associated with stigmas (Brunner et al., 2018; Dickson-Spillmann et al., 2011; Hwang et al., 2005; Kiesel et al., 2005).

5 | CONCLUSIONS

In this study, we evaluate how much consumers value clean labels and how including the name of the food technology used (a new vs. a conventional technology) affects this valuation. As a consumer, understanding the costs and benefits of a new technology compared to the standard alternative allows consumers to make informed decisions. In a between-subjects comparison, we were able to look at the effect of clean labels in two versions of a choice experiment: one in which the name of the food technology used is included and the other where it is omitted. We first employed a discrete-choice experiment using a mixed logit approach where results signaled heterogeneity in respondents. Then, to further investigate the preference heterogeneity, we estimated a latent class model.

We found that consumers responding to both survey versions (including and not including the name of the food technology used) are on average willing to pay a premium for clean labels/fewer ingredients. Respondents from the version including the name of the food technology used to sterilize shelf-stable ready meals are also willing to pay a premium for the food made with the new technology compared to the conventional technology.

Furthermore, we found that consumers are heterogeneous in their preferences for food products using new food technologies. Three classes were identified in each survey version. In the survey version not including the name of the technology used, the classes were "clean label incredulous," "moderate believers in clean labels," and "strong believers in clean labels." In the survey version including the name of the technology used, the classes were "clean label indifferent and technology takers," "moderate believers in clean labels and technology indifferent," and "strong believers in clean labels and technology indifferent."

Caveats in this study include the relatively small sample size obtained for each survey version. An improved study could include a larger response sample and the respondents' perceptions of the sensory characteristics associated with a clean label processed food product, as it is proved that flavor plays a crucial role in consumers' acceptance of foods.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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