

**REDUCING FOOD WASTE THROUGH QUALITY IMPROVEMENTS AND
INFORMATION DISCLOSURE IN THE FOOD AND BEVERAGE MARKETS**

A Thesis

Presented to the Faculty of the Graduate School
of Cornell University

In Partial Fulfillment of the Requirements for the Degree of
Master of Science in Hotel Administration

by

Paulina Alexandra Endara Pallasco

August, 2021

© 2021 Paulina Alexandra Endara Pallasco

ABSTRACT

Food waste was valued at \$285 billion in 2019, representing 70% of all food surplus; dairy and eggs alone represented 15.90%. Milk is still the fifth most consumed beverage in the U.S. despite its 14.9% decrease in consumption over the last ten years. Therefore, its impact on food waste remains relevant. Furthermore, studying consumers' behavior is pertinent to identify preferences towards technology that aims to prevent food waste. In particular, this thesis seeks to assess the willingness-to-pay for extended shelf-life, a smart tag, and an ecolabel to measure consumers' value. The three attributes have implications for preventing food waste within the milk industry. The findings suggest that consumers' valuation of extended shelf-life and an eco-certified label is positive; however, using the smart tag creates disutility for consumers. That implies retailers should find alternative means to enhance the communication of the extended shelf-life.

BIOGRAPHICAL SKETCH

Paulina was born and raised in Quito, Ecuador. She developed her passion for the hospitality industry at an early age when baking with her parents and traveling around Ecuador. Paulina majored in Hospitality Management and Finance in Universidad San Francisco de Quito. While attending college, she worked for the Walt Disney World Company in Orlando, Florida. After that, Paulina started teaching and developing hospitality and food and beverage management courses at her former university. She also worked as the Internal Control and Process Department Manager for a restaurant management company in Ecuador. Her main interest is applying her knowledge to real-world problems, so she usually helps develop small and medium hotel standard operational procedures, budgets, and marketing plans in her free time.

To my family, friends, and the loving memory of my mother.

ACKNOWLEDGMENTS

Throughout the writing of this thesis, I have received a great deal of support and assistance. When I remember all that I have gone through to be at Cornell, I cannot help but feel grateful that I had this opportunity. First and foremost, I would like to extend my sincere appreciation to my advisors: Aaron Adalja, for his valuable guidance throughout my research; and Martin Wiedmann, whose expert support and funding made this project possible.

I wish to acknowledge all my professors at Cornell who mentored me and kept me going, especially Robert Kwortnik, who convincingly guided and encouraged me through my studies. Also, Koichi Yonezawa, who helped me understand some key concepts for my research. Finally, thanks to my great loving family and the support of my friends, especially to Mauricio, Damián, and Ana Teresa, who made every effort to help me achieve my goals.

TABLE OF CONTENTS

1	INTRODUCTION.....	1
2	LITERATURE REVIEW	5
2.1	Consumer food behavior.....	5
2.1.1	Perishables	6
2.2	Food traceability.....	11
2.2.1	IoT: Internet of things and intelligent products.....	12
2.2.2	Classification of intelligent packaging	14
2.2.3	Radio frequency identification technology (RFID).....	14
2.2.4	Time-temperature indicators (TTI) integrated barcodes and RFID tags ...	15
2.2.5	Freshness indicators and gas indicators.....	16
2.2.6	Quick response (Q.R.) codes	16
2.3	Food waste	19
2.3.1	Food waste and date labeling.....	23
2.3.2	Interactions with demographics and perceptions.....	24
2.3.3	Nudging to reduce food waste.....	27
3	DATA DESCRIPTION	29
3.1	Price data	29
3.2	Survey design.....	31
3.3	Survey data collection.....	38
4	EMPIRICAL METHODOLOGY	46
4.1	Conditional logit model.....	46
4.2	Mixed logit model	48
4.2.1	Individual parameters.....	50
4.2.2	Willingness-to-pay (WTP)	50
4.3	Principal component analysis (PCA)	50
4.4	Probit model.....	51
5	RESULTS	54
5.1	Distribution of levels seen and chosen	54
5.2	Conditional logit model.....	55
5.3	Mixed logit model	58

5.4	Willingness-to-pay (WTP)	61
5.5	CHARACTERIZING HETEROGENEITY	62
5.5.1	PCA results	62
5.5.2	Interaction effects with demographics, behaviors, and perceptions.....	63
5.5.3	Exploratory analysis of WTP for each attribute.....	67
6	CONCLUSIONS.....	71
6.1	Managerial and policy implications	74
6.2	Limitations and future work.....	75
7	REFERENCES.....	76
8	APPENDIX.....	83
8.1	Appendix 1. Institutional review board for human participants: Notice of exemption.....	83
8.2	Appendix 2. Survey.....	84

LIST OF FIGURES

Figure 2.1: Sample application of an RFID tag for milk.	15
Figure 2.2: Surplus food (%) by sector - 2018.....	20
Figure 2.3: Food surplus (%) management by sector - 2018	21
Figure 2.4: Surplus food (%) by food types - 2018.....	22
Figure 2.5: Surplus food (%) by cause - 2018	22
Figure 3.1: Boxplot of prices collected for organic and conventional milk in INY.....	30
Figure 3.4: Milk bottle's design.....	32
Figure 3.5: Discrete choice experiment sample question.....	35
Figure 3.6: Information treatment sample.....	35
Figure 3.7: Explanations of attributes and levels.....	36

LIST OF TABLES

Table 2.1: Definitions of date labeling phrases.....	9
Table 2.2: Classification of intelligent packaging.....	14
Table 2.3: Summary of literature regarding value of information.....	18
Table 2.4: Summary of critical actions areas regarding food waste according to ReFED.	24
Table 2.5: Summary of literature regarding the analysis of food waste and demographic variables.....	26
Table 2.6: Summary of hypothesis.....	28
Table 3.1: Milk pricing data.	29
Table 3.2: Menu of prices to implement in the DCE experiment.	31
Table 3.3: Attributes and levels used in the choice experiments.	34
Table 3.4. List of questions regarding consumers' perceptions.	38
Table 3.5: Demographic characteristics.	40
Table 3.6: Behavioral characteristics.....	42
Table 3.7: Perception's summary.	45
Table 4.1: Variable specification for the models.	48
Table 4.2: Specification of variables for the probit model.....	52
Table 5.1: Distribution of levels seen and chosen.....	55
Table 5.2: Conditional logit parameter estimates.....	58
Table 5.3: Mixed logit parameter estimates.....	60
Table 5.4: Willingness-to-pay estimates (in USD).....	62
Table 5.5. Principal component analysis summary.	63
Table 5.6: Interaction effects with demographics, behaviors, and perceptions.	65
Table 5.7: Average marginal effects for probit regression models.....	68
Table 6.1: Summary of hypothesis and results.	74

1 INTRODUCTION

From the 229 million tons of food available in the U.S. in 2019, 35% went unsold or uneaten (ReFED, 2021). Moreover, food waste was valued at \$285 billion in 2019, representing 70% of all surplus food (ReFED, 2021). Households and customer-facing businesses are the most significant contributors to that total. In 2018, 37.2% of food waste was generated in households, 13% in retailers, and 15.8% in foodservice outlets. These statistics suggest that food waste is an ongoing concern for every stakeholder in the food supply chain. The benefits of addressing it include reducing production costs, increasing efficiency in the food system, improving food security and nutrition, and improving environmental sustainability (Patra et al., 2020).

Moreover, dairy and eggs represented 15.90% surplus food and ranked third after produce (34.30%) and prepared foods (18.80%) (The U.S. EPA, 2020). Although dairy milk consumption in the U.S. declined by 14.9% over the last ten years (Statista, 2021), it remains one of the main components of Americans' healthy diet (Wolf et al., 2020). It is the fifth most consumed beverage in the United States (Statista, 2019). In 2018, dairy products represented 20.7% of total perishable food sales after meat, seafood, and produce (Statista, 2019). Moreover, fluid milk accounted for 60.8% of total dairy department sales (Statista, 2021). Given milk's relevance, its impact on food waste drivers is relevant to study.

Consumer behavior is highly relevant to food waste prevention (Aschemann-Witzel, 2018; Bolos et al., 2019; Quested et al., 2013; Roe et al., 2018). Based on the multi-attribute utility theory, consumers choose food products based on the combination of several factors. Those factors are extrinsic (i.e., physical and chemical attributes), intrinsic (i.e., perceptions,

cognition, emotions), credence (i.e., healthiness, local, food waste), and experience (i.e., shelf-life, convenience, freshness). Consumers' valuation of those factors can either contribute to or prevent food waste. For instance, when shoppers choose products on the verge of spoiling, they effectively prevent waste (Qi & Roe, 2016; Yu & Jaenicke, 2021). On the other hand, retailers can also impact food waste. Retail stores contribute to waste by mismanaging product's inventory, handling, and rotation. Nonetheless, retailers can reduce waste by addressing consumers' reactions towards waste, highlighting the moral implications of waste, promoting the use of sensory evaluation, and educating consumers (Quested et al., 2013; ReFED, 2021).

According to the U.S. EPA (2020), spoilage ranks as the third most cited reason to dispose of food. For instance, 'millions of Americans throw out edible food because they believe it is not safe to eat it after the date on the package' (NRDC, 2017). Furthermore, consumers often perceive product freshness as continuously declining until it reaches zero by the date on the label. Therefore, most shoppers would require compensation to consume a food product close to or after that date, implying a negative price for the product. Accordingly, most consumers prefer perishable products with a longer shelf-life (Wu et al., 2017).

Consumers' confusion about the meaning of date label phrases also contributes to food waste. Shelf life is an estimate based on the producer's processing characteristics and assumptions on shipping conditions. Therefore, if dynamic environmental data is collected from the shipping point until the product reaches the final consumer, it is feasible to make dynamic changes on the shelf life using technology (e.g., smart labels). Smart labels incorporate technology that extends the functionality and content of tags or packaging beyond traditional print methods. Some of their applications include extending the shelf-life of food products and enhancing food traceability (Cierpiszewski, 2015). Moreover, retailers find them useful to

dynamically update prices, shelf-life, and other environmentally sensitive information (McFarlane et al., 2012). Thus, implementing intelligent food packaging, promoting traceability systems, and extending shelf-life while providing timely information to consumers can help reduce food waste while increasing their value perception (ReFED, 2021; Roe et al., 2018; Skinner, 2015).

This thesis aims to assess the value of shelf life, quality disclosure, and ecolabels. We implement a discrete choice experiment to determine consumers' preferences for dairy milk, estimate price premiums, and explore customers' demographics and perceptions towards relevant choice attributes. First, we determine consumers' willingness-to-pay (WTP) for milk with an extended shelf-life. Then, we establish consumers' price premium for milk with precise spoilage information by applying an intelligent label (i.e., a Q.R. code connected to temperature sensors that predict an accurate date label). Finally, by introducing an information treatment that provides facts about food waste related to milk consumption, we assess consumers' willingness-to-pay for milk with a food waste-related ecolabel.

We collected the data through a survey designed with Qualtrics' Conjoint package. The survey was divided into four sections: i) behaviors; ii) a discrete choice experiment (DCE) with variables (product attributes) and all possible levels for each choice; iii) perceptions; and (iv) demographics. The DCE section asked respondents to choose between several combinations of a one-gallon of dairy milk. The combinations were created by the Qualtrics' algorithm based on five attributes: milk type (i.e., organic compared to conventional milk), label type (static compared to smart label), additional information label (i.e., eco-certified label compared to none), date printed on the container (i.e., tomorrow, seven days from today, 18 days from today, 30 days from today), and price (i.e., \$2.55, \$3.28, \$4.39, \$5.31, \$6.28, \$7.20). We also set up a

control and a treatment group to examine whether or not information disclosure on food waste moderates consumer WTP for these attributes in milk. The treatment group received detailed information regarding food waste within the milk industry.

We launched the survey through Prolific (i.e., on-demand, self-service data collection) (Prolific, 2021) and collected 500 responses in February 2021. We analyzed the conjoint data by using the conditional and mixed logit models. Moreover, we calculated the individual WTP per attribute. We used those results to estimate a probit model of WTP greater than the sample mean (or, in the case of the smart label, positive) on demographic, behavioral, and perceptual data. The findings suggested that consumers' valuation of extended shelf-life and an eco-certified label is positive, increasing the likelihood of buying a milk bottle. However, although shoppers value the extended shelf-life, the use of a smart tag creates disutility for consumers. This implies that retailers should find alternative means to enhance the communication of the extended shelf -life.

The thesis is organized into five additional sections: (ii) literature review, (iii) data description, (iv) empirical methodology, (v) results, and (vi) conclusions, implications, and limitations. In section 2, we review the relevant literature related to the topic. Section 3 describes the discrete choice experiment's design. Then, in section 4, we develop the econometric models. Section 5 provides the results based on the models proposed in the empirical methodology. Finally, in section 6, we offer concluding remarks regarding the proposed hypothesis. We also discuss the implications of the results and provide limitations.

2 LITERATURE REVIEW

The literature review is divided into three sections: consumer food behavior, food traceability, and food waste. The first section aims to provide context related to food product selection in consumer food behavior and perishables. Then, the second section summarizes relevant information associated with the development of food traceability systems and intelligent packaging. Finally, the third section describes the stance of food waste in the U.S. and its implications with some salient factors (e.g., shelf-life, demographics, etc.)

2.1 Consumer food behavior

Behavior deals with all the potential ways people may act in their role as consumers. For example, consumer food behavior involves selecting and consuming foods and beverages while considering what, how, when, where, and with whom people eat, in addition to other aspects of their food and eating behaviors (Shepherd R., 2006). There are two main categories of attributes when selecting food (Kurajdová et al., 2019). First, intrinsic quality attributes are those related to the physical and chemical characteristics of a product. Second, extrinsic quality attributes are those related to perceptions, cognition, and emotions.

Furthermore, there are other quality attributes beyond the intrinsic and extrinsic factors. Grebitus (2006) also defined the experience and credence factors as relevant. Experience attributes are characteristics that a consumer can only verify after consuming the product, such as flavor, freshness, and shelf life. Credence factors relate to those aspects that consumers cannot identify even after consumption (Lavelli, 2013), such as healthiness, local, organic (Grebitus, 2006), country-of-origin, earth-friendly, no added hormones, etc. (Lavelli, 2013). When selecting a food product, many attributes influence consumer behavior (Kurajdová et al., 2019). For

example, some of the essential components influencing consumer preferences for perishable products are price and freshness (Li et al., 2020).

2.1.1 Perishables

Perishables are foods that, if not kept under a restricted range of environmental conditions, decay, spoil, evaporate, get damaged and become obsolete due to loss of utility or marginal value over a shorter period of time (Amorim et al., 2013). Although the management of perishable foods may seem elaborate, it is an essential strategy for retailers to attract customers (e.g., meat, dairy, produce, etc.). Therefore, perishables are highly important for a retailer (Theotokis et al., 2012). Moreover, as seen in the previous section, one of the key components to assess the quality of a product is freshness.

2.1.1.1 Product freshness and shelf-life

Product freshness is defined as the time when food's attributes (e.g., appearance, taste, etc.) are at their best. Perishable products start diminishing in quality because of several reasons that can be physically assessed. However, consumers usually rely on shelf-life (e.g., expiration dates) to determine a product's remaining 'quality.' Li et al. (2020) assert that consumers' perception of products' freshness is directly influenced by the framing and presence of date labels. Moreover, Wu et al. (2017) find that the impact of perishable products' age on demand is negative given the loss of freshness and quality.

Numerous studies have examined the implications of shelf-life when assessing the quality of a product. For example, Jedermann et al. (2014) define shelf-life as the time span food can be stored before a product starts to lose its quality. Several factors affect a product's shelf-life. In dairy milk, heat treatment directly impacts shelf-life; consequently, dairy milk can stay fresher for much longer by applying processing technologies to treat it before it reaches grocery stores.

For example, ultra-pasteurization (UP) is when milk heats for at least 2 seconds to at least 280°F. Ultra-pasteurized milk is also packaged under near sterile conditions, making re-contamination with spoilage bacteria unlikely and rare (Cornell University, 2007). That treatment is often used on organic milk as it must travel farther to reach store shelves than conventional milk (Smith et al., 2009). Therefore, the shelf-life for organic dairy is often longer than that of conventional milk.

On the other hand, conventional milk is mostly pasteurized with one of two standard pasteurization procedures, low-temperature-long-time (LTLT) or high-temperature-short-time (HTST). LTLT heats milk to 145°F for at least 30 minutes, while HTST heats milk to 160°F for at least 15 seconds. Those procedures effectively kill spoilage microorganisms in the milk (Schwendel et al., 2015). Nevertheless, since both treatments are gentler than UP, shelf-life remains shorter. In addition, the product's quality also depends on the processing and environmental conditions along the supply chain (i.e., time and temperature changes from distribution, storing, etc., at retailers and home). For instance, the date label would dynamically change given the environmental changes from shipping until reaching the retailer/end consumer.

2.1.1.2 Date labels

Date labels on food aim to inform consumers and retailers the last date products are at their peak quality and flavor; thus, they reflect quality rather than food safety (The Food and Drug Administration). Likewise, in terms of consumer behavior, a date label would constitute an attribute that defines the product's value or signals the product's quality (Theotokis et al., 2012).

Given that date labels are not required by Federal Law (i.e., except for infant formula) (U.S. Department of Agriculture), they mainly reflect a quality decrease below an acceptable

limit set by the manufacturer, but not a reduction of products' safety and wholesomeness (Roe et al., 2018).

One implication of date labels is that they may suggest that the product's quality remains stable until that specific date. Hence, many consumers believe that products abruptly lose quality after that date and are no longer fit for consumption (Li et al., 2020). On the contrary, products gradually decrease their quality or freshness before and after the expiration date (Li et al., 2020). Moreover, as the FDA and other researchers insist, date labels relate to quality rather than safety; therefore, food would spoil or be unsafe to eat after a long time after the set date on the package (Minor et al., 2019).

Additionally, the inconsistency of current labeling practices adds to the confusion between 'sell by,' 'best by,' 'use-by,' and 'best before' dates (Neff et al., 2019; ReFED, 2021; Roe et al., 2018; Thompson et al., 2018; Wilson et al., 2017, 2019; Yu & Jaenicke, 2021). Table 2.1 summarizes the meaning of each of those terms. The misunderstanding of current labeling practices leads consumers to dispose of food that is still safe to consume, holds nutritional value and has acceptable flavor (Newsome et al., 2014; ReFED, 2021). Date labels would increase consumers' willingness to accept consumption within that date. Still, their perception of quality rapidly changes after products reach that date compared to products without an expiration date (Li et al., 2020).

Table 2.1: Definitions of date labeling phrases.

Date labeling phrase	Meaning
‘Sell by’	It conveys to the retailer the last date the product can be displayed for sale. It does not signal products’ quality or safety.
‘Best if used by,’ ‘Best before,’ ‘Best by’	They ‘suggest the date after which the food’s quality or flavor may deteriorate.’
‘Use by’	It ‘recommends the last date by which the product should be consumed but does not necessarily convey safety information.’

Source: (Tsiros & Heilman, 2005).

Roe et al. (2018) develop a multivariate analysis to assess the discard intentions of dairy milk without date labels. They find that consumers rely on smelling and visualizing to determine whether to discard products when there is no date label. Furthermore, they find that the perceived acceptability, healthfulness, and freshness diminishes between milk dated a day before and a day after, but the risk and safety ratings do not change (Roe et al., 2018). These findings suggest that sensory evaluation is relevant when deciding whether to discard milk as it is a salient indicator to discern products’ quality (Ellison & Lusk, 2018). However, educating consumers on date labeling is required as some may still discard milk even when it smells fine (Ellison & Lusk, 2018). As a result, retailers have implemented discounting strategies to decrease food waste.

2.1.1.3 Shelf-life and pricing

Grocery retailers often reduce the price of perishable products following their remaining shelf-life; that practice is called expiration date-based pricing (EDBP) (Aschemann-Witzel, 2018; Theotokis et al., 2012; Tsiros & Heilman, 2005). Discounting perishables (e.g., bottles of milk) as they approach their date label seems appropriate. Given that previous literature shows that consumer's utility, and thus their willingness-to-pay (WTP), decreases for milk with shorter shelf life (Thompson et al., 2018), while their willingness-to-accept (WTA) increases (Li et al.,

2020). The relationship between shelf-life and customers' perception of price allows retailers to apply revenue management concepts to perishables. Discounting has been widely used by retailers to stock out products about to reach the date label. Some implications regarding this practice have been analyzed in consumers' perception of trust and loyalty towards retailers implement discounting (Theotokis et al., 2012).

Li et al. (2020) studied perishables within hedonic markets to evaluate how shoppers value perishables and respond to a series of labeling systems. Their study discovered that WTA decreases in the presence of expiration dates compared to none (i.e., products without labels) if consumed before the date label. Previous studies show that there is a discontinuous change in preference immediately after the listed date. Therefore, it has been suggested that retailers consider offering discounts on the day after the 'expiration date.'

Some benefits of extending shelf-life for perishable products, such as milk, are maximizing the retailer's profit and optimizing inventory. When analyzing inventory models for perishable products, Wu et al. (2017) explore the relationship between the selling price and the length of the inventory period. They find that if a retailer has many potential customers, both the price and the inventory period's length should increase to maximize the retailer's profit. Furthermore, extending the shelf life of products can help reduce food waste (ReFED, 2021; Roe et al., 2018). These findings suggest that there is an explicit tradeoff when setting date labels for perishable products. If the date is set too short, the retailer/consumer may dispose of sound products.

On the other hand, if the date is set too long, the retailer may sell low-quality food, and the consumer may decrease their trust in a specific brand (Li et al., 2020). Consequently, consumers benefit from discounted perishables as they can make tradeoffs between higher and

lower-margin products. However, consumers may perceive discounted products as riskier since they are closer to their label date (Theotokis et al., 2012).

All in all, the benefits of extended shelf life seem to outweigh the drawbacks. Therefore, drawing upon these findings, our first hypothesis is:

H₁ (Value of shelf life): Consumers are willing to pay more for milk with longer shelf life, *ceteris paribus*.

2.2 Food traceability

Food traceability is the ability to trace and track the information and movement of food products (including their ingredients) throughout all the stages of the food supply chain (i.e., backward and forward). It entails connecting and documenting food products' production, processing, and distribution (The Food and Drug Administration, 2020). Lavelli (2013) defines traceability as being capable of tracking a product's history location regarding its production materials (e.g., ingredients, raw materials), related information (e.g., quality and safety specifications), and interested parties.

This system is also known as the tracing and tracking of information from farm-to-fork. Thus, a traceability system has two main functions: tracking and tracing.

- *Tracking* refers to the ability to follow products upstream (i.e., suppliers and processes to manage relationships with them) and downstream (i.e., distribution and delivery) in the supply chain (Pizzuti et al., 2014).
- *Tracing* refers to the reversed process by which a system retrieves the recorded information along the supply chain and delivers information to the user (i.e., retailer,

customer, supplier, etc.) (Pizzuti et al., 2014). The kind of retrieved information will be dependent on the users' intentions. For instance, a customer/retailer may be interested in retrieving the product's actual origin, changes in temperature, shelf life, etc.

Implementing traceability systems that provide valuable information to consumers is critical to the U.S. food system. Food traceability has been required in the U.S. since 2002 when Congress passed the Bioterrorism Act, by which 'one-step forward and one-step-back' accountability within the food supply chain was needed (Public Health. Security and Bioterrorism Preparedness and Response Act of 2002). Then, in 2011, the FDA was granted the authorization to require a full traceability record for certain food products (i.e., high-risk); thus, improving the capacity to detect and respond to food safety problems (US FSMA, 2011). However, the U.S. still lacks a coordinated system to implement traceability from farm-to-fork (The Food and Drug Administration, 2020).

The information flow among all food supply chain stakeholders is critical to optimize resource use and cost. Some of the key benefits of product traceability are increased product safety and quality and consumers' trust (Tarjan et al., 2014). Lavelli (2013) lists the functions of traceability systems as addressing safety risks, attaining shopper's trust, and encouraging quality improvement. Some of the efforts executed regarding food traceability include those developed within the Internet of Things (IoT).

2.2.1 IoT: Internet of things and intelligent products.

The Internet of Things (IoT) aims to remotely perceive and control items, then combine them with the Internet and create wiser production and living systems (Badia-Melis et al., 2015). It makes the infrastructure to ease the exchange of information (Kiritsis, 2011). Intelligent food

logistics and smart products are designed to interact in this environment. Intelligent food logistics aims to diminish food waste by minimizing deviations from the optimal cold chain. Some actions to make that happen are quantifying those deviations by using intelligent products along the supply chain and making shelf-life variation remotely monitored and controlled (Y. Y. Chen et al., 2014). Some tools of IoT that could help with those actions are intelligent products.

Intelligent or smart products combine two components: a physical and an information-based one. The communication between both elements is achieved through a tag and a reader (McFarlane et al., 2012). Some key characteristics of these products are the ability to communicate with the user, react to environmental conditions, and consistently monitor their status and environment (Kiritsis, 2011). There are two levels of product intelligence. The first one allows the product to communicate its status (e.g., location, composition, etc.), so the function is informative. The second one allows the product to communicate its state and assess and influence its operation (e.g., self-distributing inventory, self-manufacturing inventory, etc.), so the function is decision-oriented (Wong, et al., 2002). Therefore, these products comprise an essential part of intelligent packaging.

Intelligent or smart packaging is defined as packaging materials with the ability to perceive and process characteristics and properties from the food it carries and the surrounding environment (Müller & Schmid, 2019). These products can inform the manufacturer, retailer, and consumer of the state of these properties (Cierpiszewski, 2015). The benefits of intelligent packaging are linked to consumer trends (e.g., sustainability, product safety, high-quality standards, etc.) (Tsiros & Heilman, 2005). For example, smart labels contribute to more efficient product quality monitoring, tracing critical control points, and providing more detailed information throughout the supply chain (Cierpiszewski, 2015).

2.2.2 Classification of intelligent packaging

Intelligent packaging can be divided into three categories based on its function: data carriers, indicators, and sensors. Table 2.2 summarizes the functions and examples of each type of intelligent packaging.

Table 2.2: Classification of intelligent packaging.

Type	Function	Examples
Data carriers	To enhance the information flow's efficiency (e.g., storage, distribution, etc.) instead of quality monitoring.	Barcodes, two-dimensional barcodes: Q.R. codes, and RFID (Radio frequency identification technology), Time-temperature indicators (TTI) integrated barcodes and RFID tags.
Indicators	To determine the presence, absence, and reactions of substances	Time-temperature indicators (TTI), freshness indicators, and gas indicators.
Sensors	To send a cue when a certain physical or chemical property is perceived.	Gas sensors, chemical sensors, and biosensors.

Source: (Müller & Schmid, 2019).

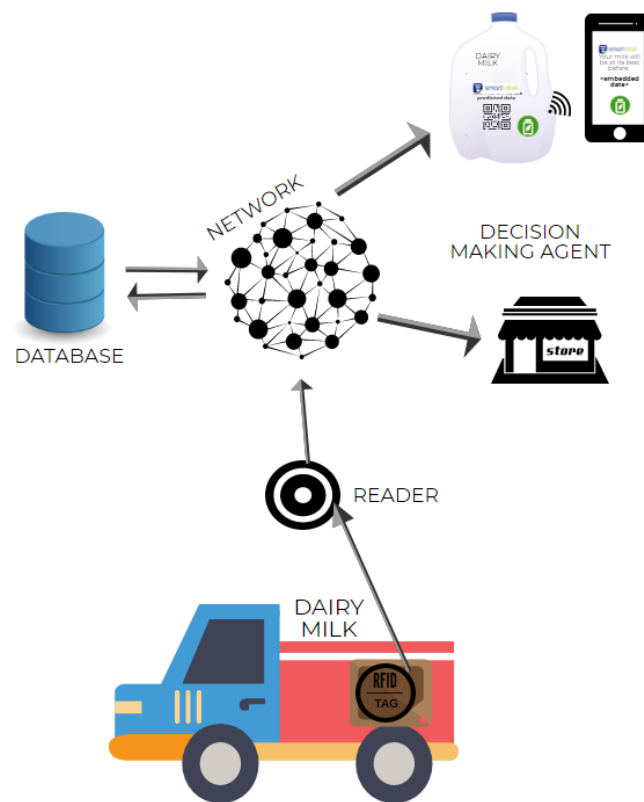
The types of intelligent packaging mostly applied in the food industry are quick response codes, radio frequency identification (RFID) tags, time-temperature indicators (TTI) integrated barcodes and RFID tags, freshness indicators, and gas indicators.

2.2.3 Radio frequency identification technology (RFID)

RFID employs fasten tags to packaging or logistics tools (e.g., pallets, containers, cattle) to send real-time, accurate data to a decision-making agent (i.e., system's user) (Cierpiszewski, 2015). Figure 2.1 represents a sample system applied to the milk food supply chain. The system presents three components. The first one is an RFID tag (i.e., it usually has a microchip attached to an antenna). The second one is a reader that emits and collects signals from the tag. Finally, the third one is a network (middleware) that connects the RFID hardware with the decision-making agent (e.g., a customer retrieving information from a Q.R. code attached to the RFID

tag). The high cost of these devices presents a limitation when applying it to low-margin food products (e.g., pasteurized cow's milk) (Gaukler & Seifert, 2007). They are more expensive than Q.R. codes, but these devices present several advantages to the food supply chain. Some of those advantages are: promoting quality and safety and enhancing traceability and inventory management (Gaukler & Seifert, 2007).

Figure 2.1: Sample application of an RFID tag for milk.



Source: Based on (McFarlane et al., 2012)

2.2.4 Time-temperature indicators (TTI) integrated barcodes and RFID tags

These tags transfer static information and the temperature progression of a product (Müller & Schmid, 2019). When assessing shelf life, the temperature is a critical factor because temperature disparity may promote microorganisms' growth or survival. Those agents may

induce the product to spoil (Müller & Schmid, 2019). These spoilage sensors are indicators that react to different factors, such as variations on time and temperature, chemical compounds, electrochemical changes, enzymatic activity, or even microbiological changes of a food product. These spoilage sensors come in different form factors, from color-changing labels to electronic devices (Müller & Schmid, 2019). Typically, the information can be visually perceived (e.g., changes in color or mechanical alterations).

2.2.5 *Freshness indicators and gas indicators*

Freshness indicators assess product changes in quality during shipment and storage (Müller & Schmid, 2019). In addition, they usually transfer information regarding the growth of microorganisms or chemical changes (Müller & Schmid, 2019). Moreover, gas indicators assess the food's status regarding the indoor atmosphere (i.e., changes inside the packages) (Müller & Schmid, 2019).

2.2.6 *Quick response (Q.R.) codes*

Quick response (Q.R.) codes are two-dimensional barcodes that encrypt information. Q.R. codes are easy to implement as they have the following benefits (Tarjan et al., 2014):

- Enough storage capability,
- Good readability, even on small-sized labels,
- Good readability, in case of physical damage,
- Low cost.

Regardless of the benefits of Q.R. codes, consumers still fail to use them. For instance, Kim & Woo (2016) applied the technology acceptance model (TAM) to assess people's behavioral intentions using Q.R. codes that show information regarding food traceability. The TAM is

supported by the relationships among beliefs, attitudes, and behaviors, in that order. Therefore, before engaging in a behavioral intention, an attitude toward using the technology must be constructed from preconditions such as individuals' perceived usefulness and perceived ease of use.

The perceived usefulness is enhanced when the information is valuable to the user. Also, the value of this information correlates with the level of involvement of each individual with the product. Consequently, customers' value perception increases when the information appeals to their motives and is easy to understand. As a result, consumers develop a better attitude towards using the new technology. On the other hand, increasing the new technology's perceived usefulness (i.e., providing relevant information) and designing intuitive, easy-to-access platforms will encourage users to adopt the technology (Kim & Woo, 2016). Table 2.3 summarizes the literature regarding the value of information.

Table 2.3: Summary of literature regarding value of information.

Authors	Findings	Data	Method
(Amoako-Gyampah, 2007)	Users' perception of the perceived usefulness, ease of use of the technology, and the user's level of intrinsic involvement affect their intention to use the technology.	A mail survey well-validated and reliable administered to 1562 participants in several U.S. regions.	Multiple regression analyses
(Lee et al., 2015)	Food manufacturers should focus on technology information as a selling point given that this information strongly influences products' expectations and acceptance.	One hundred and eighteen consumers of Chinese ethnicity from mainland China living in New Zealand.	Analysis of variance (ANOVA) and the Tukey's HSD test.
(Stolzenbach et al., 2013)	Local producers should focus on product information as a selling point as this information strongly influences preferences (i.e., liking).	A total of 183 apple juice consumers from Denmark.	Paired t-test multivariate data analysis.
(M. F. Chen & Huang, 2013)	The higher the degree of involvement individuals have, the more a food traceability system mitigates their perceived uncertainty.	A study conducted in Taiwan, and a total of 435 valid subjects collected.	Structural model analysis chi-squared.

In summary, consumers' attitude towards traceability systems is positive as it creates transparency in the food supply chain. Therefore, intelligent products are suitable tools to implement technology for traceability systems. Thus, drawing upon these findings, the second hypothesis in our study is:

H₂ (Value of quality disclosure): Consumers are willing to pay more for milk with precise spoilage information, *ceteris paribus*.

2.3 *Food waste*

Food waste has an environmental, economic, and social impact (Minor et al., 2019). In addition, it is a current consumer trend within the food industry as shoppers account for their food choices' social and environmental impact. A considerable literature has been published on food waste (Aschemann-Witzel, 2018; Bolos et al., 2019; Ellison & Lusk, 2018; Jedermann et al., 2014; Minor et al., 2019; Patra et al., 2020; Richter & Bokelmann, 2018; Roe et al., 2018; Thompson et al., 2020; Wilson et al., 2017, 2019; Yu & Jaenicke, 2021). However, there is still a degree of uncertainty around its definition and measurement. According to previous studies, reports, and government organizations, Thyberg & Tonjes (2016) provided a list of food waste definitions. For instance, The United Nations Environment Programme (2021) defines food waste as:

“food and associated inedible parts removed from the human food supply chain in the following sectors: manufacturing of food products; food/grocery retail; food service; and households. Removed from the human food supply chain means it will have one of the following destinations: landfill, controlled combustion, sewer, litter/discards/refuse, co/anaerobic digestion, compost/aerobic digestion, or land application.”

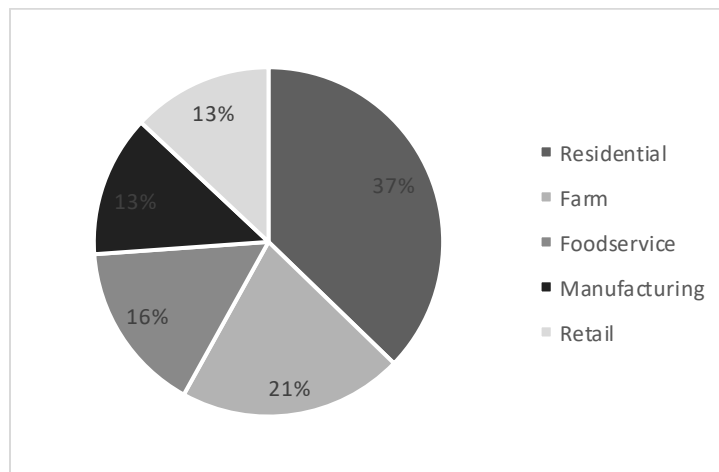
Similarly, Thyberg & Tonjes (2016) define food waste and food loss depending on the origin of the food surplus (i.e., food that has been leftover and most likely will be discarded in landfills, donations, animal feed, etc.):

- Food waste refers to food produced initially for human consumption but then discarded or uneaten. The residential and commercial sectors generate it, and its drivers are decisions made by consumers and businesses, quality, aesthetic, or safety standards.

- Food loss refers to edible food mass that decreases through the food supply chain. It is generated by the production, post-harvest, and processing sectors. Its drivers are drawbacks in infrastructure, climate, environmental factors, quality, aesthetics, or safety standards.

The current study focuses on food waste, as defined by Thyberg & Tonjes (2016). As seen before, the impact of food waste in the U.S. is significant. Food waste occurs at every stage of the food supply chain. However, as shown in Figure 2.2, most food waste happens at consumer-facing businesses (13% at retail and 15.80% at foodservice) and households (37.20%) (ReFED, 2021).

Figure 2.2: Surplus food (%) by sector - 2018

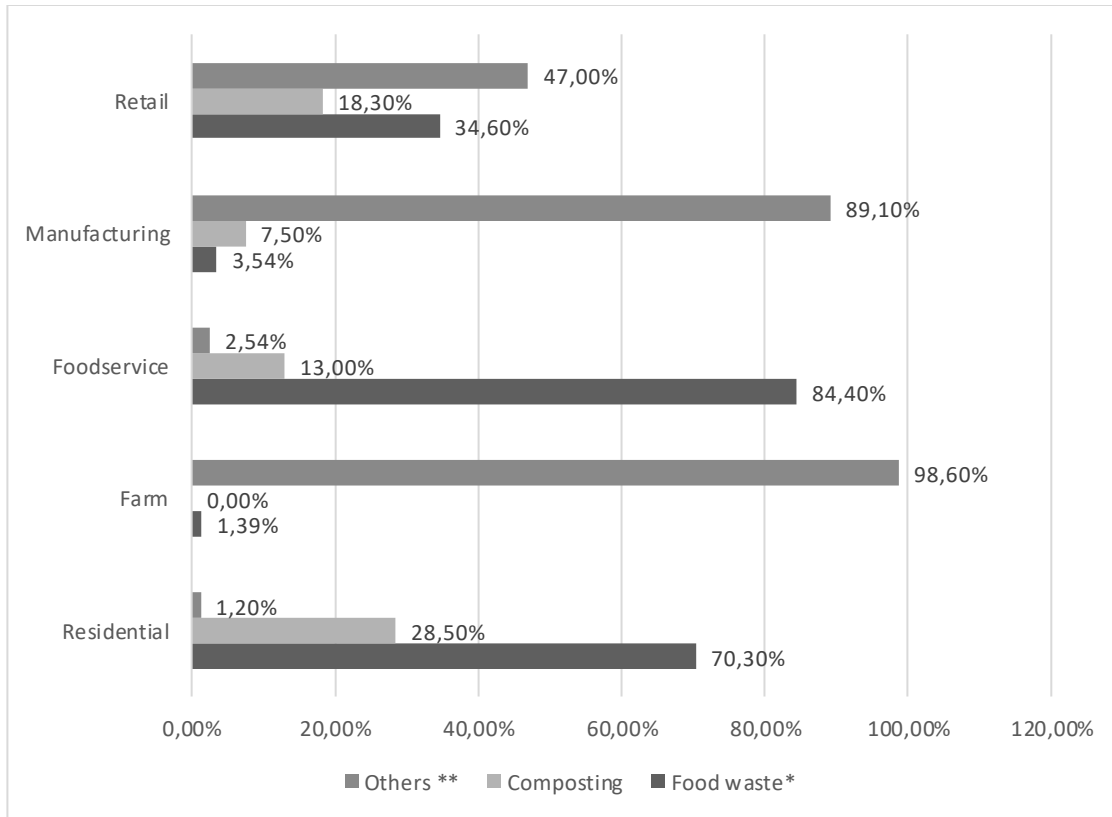


Source: (The U.S. EPA, 2020)

The management of food surplus is usually classified into three categories. The first one is food waste (i.e., the excess that ends up in landfills), followed by composting, and others (i.e., food not harvested, dumping, donations, anaerobic digestion, land applications, and industrial uses). Most food surplus from residential and commercial sectors ends up in landfills. Figure 2.3 shows the distribution of food surplus management by sector. As shown, most food surplus from

the residential (70.30%) and food service (84.40%) sectors ends up buried in landfills. Most of the retailer’s food surplus also ends up as food waste (34.60%).

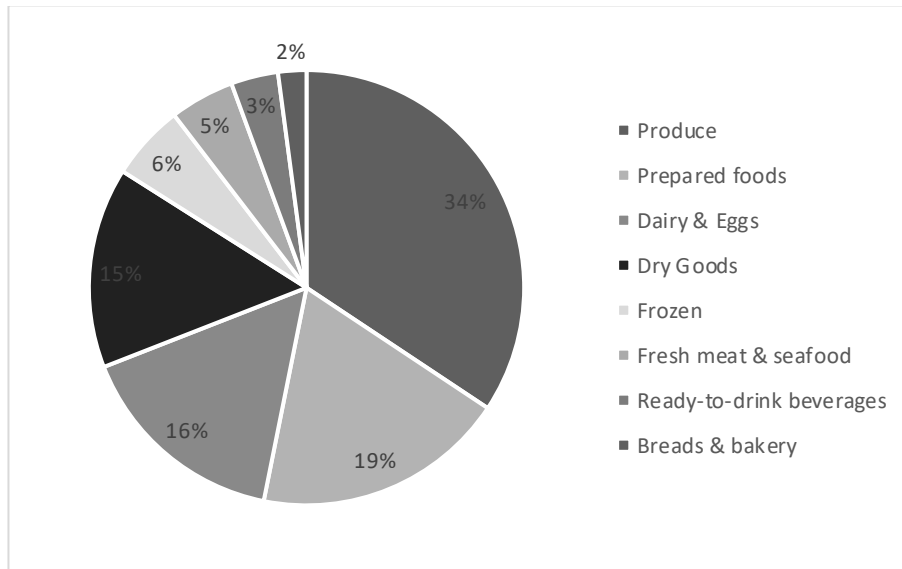
Figure 2.3: Food surplus (%) management by sector - 2018



Notes: *Food waste includes landfill, incineration, and sewer. **Others include not harvested, dumping, donations, anaerobic digestion, land application, and industrial uses. Source: (The U.S. EPA, 2020)

Figure 2.4 shows the share of surplus food for each food type. Dairy and eggs represented 15.90% surplus food and ranked third after produce (34.30%) and prepared foods (18.80%).

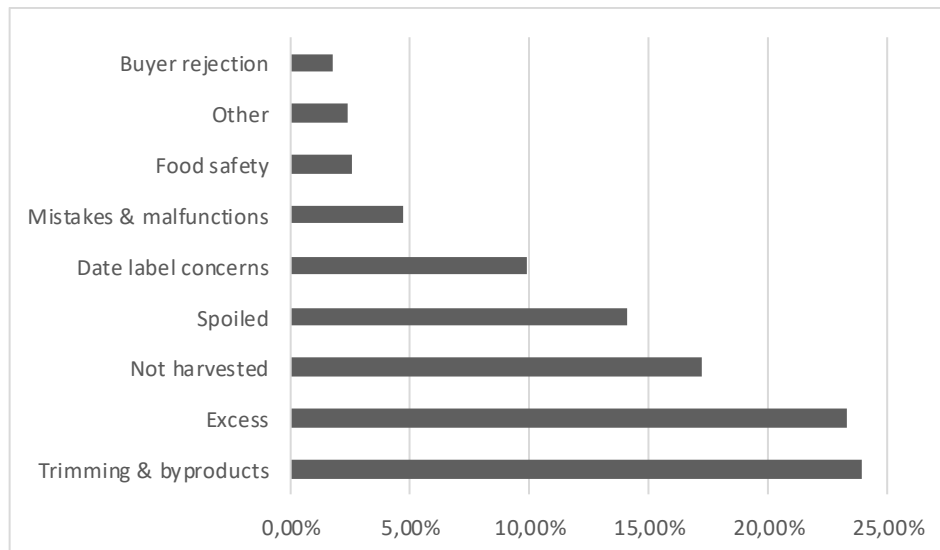
Figure 2.4: Surplus food (%) by food types - 2018



Source: (The U.S. EPA, 2020)

Figure 2.5 shows the highest-ranked causes of surplus food in the U.S. The ones ranked at the top are trimming & byproducts, excess, not harvested, spoiled, and date label concerns (ReFED, 2021).

Figure 2.5: Surplus food (%) by cause - 2018



Source: (The U.S. EPA, 2020)

2.3.1 Food waste and date labeling

Suboptimal products deviate from 'optimal' due to their appearance, date labeling, and packaging (De Hooze et al., 2017). Moreover, previous studies indicate that the WTP diminishes with the extent of the remaining shelf-life (e.g., consumers waste food at home because it has passed the 'expiration' date). Thus, consumers tend to choose products with the longest remaining shelf-life (De Hooze et al., 2017). Consequently, discarding products that may be close or past the expiration date contributes to food waste.

As previously discussed, one approach retailers can use to address this issue is discounting. However, there is still a need to expand the efforts. For instance, Rethink Food Waste through Economics and Data (2021) reported a list of initiatives to reduce food waste by 50% until 2030. Table 2.4 summarizes each initiative and presents sample modeled solutions for each key action. Each stakeholder along the food supply chain (i.e., producers, manufacturers, retailers, foodservice, policymakers, and capital providers) is responsible for those initiatives, though most strategies are multi-disciplinary.

Table 2.4: Summary of critical actions areas regarding food waste according to ReFED.

Key action area	Description	Modeled solutions
Optimize the harvest	<ul style="list-style-type: none"> • Avoid overproduction. • Harvest as much as possible. • Source only the required number of wild-caught products. 	<ul style="list-style-type: none"> • Imperfect & surplus produce channels. • Buyer specification expansion. • Gleaning. • Partial order acceptance.
Enhance product distribution	<ul style="list-style-type: none"> • Leverage technology to create smart systems that help efficiently move products to maximize freshness and selling time. 	<ul style="list-style-type: none"> • Intelligent routing. • First expired, first out. • Temperature monitoring (pallet transport).
Refine product management	<ul style="list-style-type: none"> • Align purchases with sales. • Develop systems and processes for optimal on-site handling. 	<ul style="list-style-type: none"> • Enhanced demand planning. • Dynamic pricing. • Minimized on hand inventory. • Decreased minimum order quantity. • Temperature monitoring (Foodservice).
Maximize product utilization	<ul style="list-style-type: none"> • Design facilities, operations, and menus to maximize the use of each product. 	<ul style="list-style-type: none"> • Active & intelligent packaging.
Reshape consumer environments	<ul style="list-style-type: none"> • Promote environments that drive consumers towards better food management and less waste. 	<ul style="list-style-type: none"> • Portion sizes. • Consumer education campaigns. • Package design. • Standardized date labels.
Strengthen food rescue	<ul style="list-style-type: none"> • Increase capacity, address bottlenecks and improve the communication flow. 	<ul style="list-style-type: none"> • Donation education. • Donation value-added processing.
Recycle anything remaining	<ul style="list-style-type: none"> • Optimize the use of the remaining food. 	<ul style="list-style-type: none"> • Centralized composting. • Home composting. • Livestock feed.

Source: (ReFED, 2021).

Notes: The highlighted elements on the table relate to the current thesis aim.

2.3.2 Interactions with demographics and perceptions

Decreasing food waste requires the efforts of all stakeholders along the food supply chain, including consumers. However, there is heterogeneity in how consumers approach food waste (Ellison & Lusk, 2018). Moreover, research has shown that personal factors also

influenced consumers' food waste behavior (De Hooge et al., 2017). Table 2.5 summarizes the literature regarding interactions between food waste behavior and demographics. For instance, gender, age, household composition, and household income seem to affect food waste.

On the other hand, education does not show an apparent effect. Additionally, Richter & Bokelmann (2018) used the means-end-chain method to assess how feelings and attitudes impact people's behavior towards food waste. They concluded that food waste is personally important as most consumers attested to experience a bad conscience given that wasting food is perceived as morally wrong (Richter & Bokelmann, 2018).

Table 2.5: Summary of literature regarding the analysis of food waste and demographic variables.

Authors	Variable	Findings	Method	Product
(Katajajuuri et al., 2014)	Gender	Food waste was higher when women were responsible of grocery shopping.	Linear regression model.	General household food products
(Koivupuro et al., 2012)	Gender	Food waste was higher when a woman was responsible for groceries.	Linear regression model.	General household food products
(Canali et al., 2017)	Age	Food waste was higher on the young age of household members and young couples with small children.	Cross-contextual prioritization.	General household food products Food service
(Quested et al., 2013)	Age	Food waste was lower in the over 65 age group.	Correlation	Spaghetti soup
(Stefan et al., 2013)	Age	Age correlated negatively.	Two stages empirical analysis. Confirmatory factor analysis and structural equation model.	General household food products
(Qi & Roe, 2016)	Household composition	Single households waste more food.	Expert interview with a model of the potential relations.	General household food products
(Koivupuro et al., 2012)	Household composition	Positive correlation with the number of people.	Linear regression model.	General household food products
(Quested et al., 2013)	Education	No clear correlation with education.	Correlation.	Spaghetti soup
(Stefan et al., 2013)	Household income	Positive correlation with household income.	Two stages empirical analysis. Confirmatory factor analysis and structural equation model.	General household food products
(Buzby & Hyman, 2012)	Household income	Higher-income households tend to waste more food.	Review.	General household food products

2.3.3 *Nudging to reduce food waste.*

Nudging is a widely used technique to influence food consumer behavior. A nudge is the change in the way choices are presented, predictably altering behavior without forbidding any options or significantly changing economic behaviors (Bolos et al., 2019). The classical classification of mental activities includes cognition, affect, and behavior (Cadario & Chandon, 2020). In that sense, there are three categories for the intervention of information:

1. **Attention-focused intervention:** Those are cognitively oriented interventions that aim to influence consumers' knowledge (Cadario & Chandon, 2020) through providing products' descriptions (e.g., visuals of product characteristics, colors) or affecting store's visibility (e.g., the specific layout of products) (Bolos et al., 2019).
2. **Interest-focused intervention:** Those are affectively oriented interventions that aim to influence consumers' feelings without altering their knowledge (Cadario & Chandon, 2020). It appeals to people's emotions by using engaging messages (e.g., vivid sensory descriptions, wholesome packaging, photos) (Bolos et al., 2019).
3. **Action-focused intervention:** Those are behaviorally oriented interventions that aim to influence consumers' actions without altering their knowledge and feelings (Cadario & Chandon, 2020). It implements means unaware to the consumer (Bolos et al., 2019)—for instance, decreasing portion sizes.

The effectiveness of each intervention increases as they move from attention to interest to action (Cadario & Chandon, 2020). For example, attention-focused interventions proved to be more effective in a retail setting as consumers can react to specific information regarding food waste (e.g., amount of carbon emissions caused by food, etc.) Action-focused interventions, such as extending the shelf life of dairy milk, should also be more effective.

Retailers and researchers have used information treatments to influence consumer behavior. Scozzafava et al. (2020) studied the impact of four information treatments (i.e., animal welfare, food quality, environmental sustainability, and the higher cost of organic products compared to conventional ones) on consumer preferences for milk. They find that animal welfare and environmental sustainability increased the willingness to pay for organic compared to conventional milk. Therefore, retailers could use those motivators to promote products with such characteristics, as those positively impact consumers' preferences when printed on the packaging or shared through other means (Scozzafava et al., 2020). Thus, given the relevance of food waste for retailers and customers, our third hypothesis is:

H₃ (Value of ecolabels): Consumers are willing to pay more for milk in the presence of a food waste-related ecolabel, *ceteris paribus*.

Table 2.6 shows a summary of the three proposed hypotheses based on the previous literature review.

Table 2.6: Summary of hypothesis.

Hypothesis	
H₁. Value of shelf-life	Consumers are willing to pay more for milk with longer shelf life, <i>ceteris paribus</i> .
H₂. Value of quality disclosure	Consumers are willing to pay more for milk with precise spoilage information, <i>ceteris paribus</i> .
H₃. Value of ecolabels	Consumers are willing to pay more for milk with a food waste-related ecolabel, <i>ceteris paribus</i> .

3 DATA DESCRIPTION

This section is divided into three parts: (i) price data, (ii) survey design, and (iii) survey data collection.

3.1 Price data

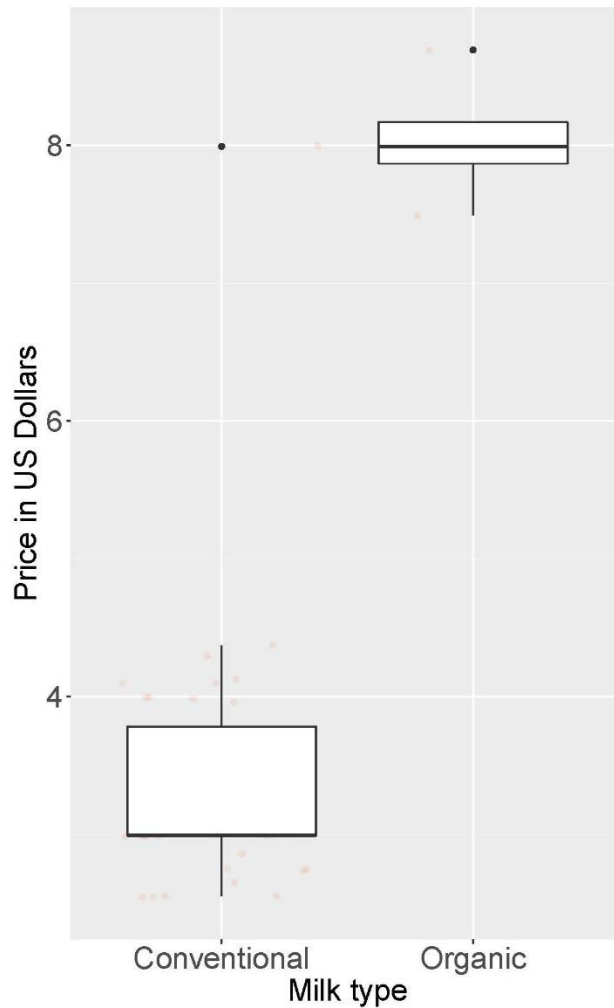
Primary data regarding dairy milk prices were collected from grocery retailers to determine a menu of prices for the discrete choice experiment. Data were collected online and in-person in Ithaca, New York, during June 2020. The information gathered is listed in Table 3.1.

Table 3.1: Milk pricing data.

Description	
Retailer	Aldi, BJ's, Greenstar, P&C Fresh, Tops, Walmart, & Wegmans.
Type of milk	Conventional, organic, almond, buttermilk, cashew, coconut, goat, lactose-free, hazelnut, walnut, oat, pea, soymilk.
Brand	Private labels, A2, Almond Breeze, Byrne Dairy, Califia farms, Cornell Dairy, Creamline, Dream, Elmhurst, Fairlife, Friendly Farms, Full Circle, Great Value, Green Gout, Hillcrest Dairy, Ithaca Milk Cream on Top, Lactaid, Living Harvest Tempt, Maple Hill, Organic Valley, Parmalat, Planet Oat, Ripley Family, Silk, Simply Nature, Stonyfield, Tops, Upstate Farms, Wallaby, Wellsey Farms.
Size	One-gallon, half-gallon, quart.
Fat content	Skim, 1% low-fat, 2% reduced-fat, whole.

The menu of prices was designed based on one-gallon dairy milk as it is the most consumed in the U.S. (USDA, 2020). From the information collected, 45 data points correspond to one-gallon conventional and organic milk bottles. Figure 3.1 shows the distribution of prices for both kinds of milk.

Figure 3.1: Boxplot of prices collected for organic and conventional milk in INY.



Given the limited sample of one-gallon organic milk in the Ithaca area, the average prices reported by the USDA for a gallon of milk were included as part of the menu of prices to avoid distribution errors. Table 3.2 presents the menu of prices to be implemented in the discrete choice experiment. The prices are based on the cumulative frequency distribution of the collected data points.

Table 3.2: Menu of prices to implement in the DCE experiment.

Price	\$	Increment over the previous price
Price 1	2.55 ³	-
Price 2	3.28 ¹	29%
Price 3	4.21	28%
Price 4	5.13	22%
Price 5	6.28 ²	22%
Price 6	7.20 ⁴	15%

¹Average price for a gallon of conventional milk (USDA, 2020).

²Average price for a gallon of organic milk (USDA, 2020).

³Min value from sample prices.

⁴Max value from sample prices.

3.2 Survey design

The methodology employed in our research design is a stated preference choice experiment through a survey instrument consisting of four parts: i) behaviors; ii) a discrete choice experiment (DCE) with variables (product attributes) and all possible levels for each choice; iii) perceptions; and (iv) demographics. We set up a control and an equally balanced treatment group. Based on the nudging technique, a cognitive and attention nudge was shown to customers in the treatment group to examine whether or not information disclosure about food waste moderates consumer behavior. The information treatment was a passage with statistics about food loss and waste and a message to capture shoppers' attention. An example of the information card is in Figure 3.4. Respondents in the control group did not see the information card. A complete copy of the survey is included in Appendix 2. Survey.

The first part of the survey aimed to gather information on consumer purchase behavior for pasteurized cow milk—buying frequency, consumption rate, fat content, labeling, lactose-free, location of purchase, non-dairy alternatives, purchasing rate, and milk size. The second part

of the survey was the DCE. Respondents were asked to imagine they were in their favorite grocery store, looking to purchase one gallon of dairy milk. They were also asked to assume any product attribute not listed on each page was identical across all purchase options (e.g., type of container, package size, and fat content are all the same across options).

The goal of the DCE section was to test consumers' preference for a milk bottle that has a smart tag that collects up-to-date data from temperature sensors throughout the milk's supply chain and predicts a more accurate date label. Based on the intended design, the milk bottle would have a smart tag and an ecolabel. Shoppers would need to scan the Q.R. code with a smartphone to access the 'embedded date,' which will be assessed and updated in real-time. Figure 3.2 represents a sample milk bottle's design.

Figure 3.2: Milk bottle's design.



Four DCE questions were presented to each respondent. Each DCE question consisted of a discrete choice between three one-gallon milk products characterized by the attributes shown in Table 3.3. We selected five features, including price, to mimic a customer's in-person experience when buying milk. First, we set conventional (i.e., pasteurized cow's milk) and organic milk

under the milk type feature. We chose organic as a control variable due to its market relevance (Hasselbach & Roosen, 2015; Scozzafava et al., 2020). For instance, in 2018, 24% of consumers said organic labels mattered a lot when shopping for dairy products (Statista, 2018). Moreover, consumers choose organic milk because it is healthier, wholesome, reminiscent of the past, and fashionable; tastes better; addresses environmental, food safety, and animal welfare concerns; and supports the local economy (Hughner et al., 2007).

Then, two kinds of label types were included: static and smart. A static label is printed on the package by manufacturers. On the other hand, a smart label is a Q.R. code that asks respondents to scan it to find the predicted spoilage date for the product. Hypothetically, once customers scan it, it will show an embedded date label based on up-to-date data collected from temperature sensors throughout the milk's supply chain.

Next, we include an additional information label attribute consisting of the presence or absence of a food-waste-related ecolabel. As stated before, the control group only sees the ecolabel's logo, whereas the treatment group reads the information card (Figure 3.4). The goal of the eco-certified label is to disclose information regarding the products' food waste impact. For instance, we included facts and a message to appeal to shoppers' attention and interest. Fourth, a date label attribute was presented as "date printed on the container" to avoid confusion about the meaning of existing date labels. Therefore, consumers rely on their existing beliefs about the meaning of the shelf-life date when evaluating this attribute. Four date levels were selected to test the shopper's preference for extended shelf life. Those levels were determined based on the average consumption rate of milk in American households and differing across state regulations (Yu & Jaenicke, 2021). For instance, based on the literature review, people would require a discount to consume starting the next day after the date on the package. Thus, 'tomorrow' was

selected to control for that effect. Based on the overall annual consumption milk rate, Americans buy milk approximately 28.4 times (on average) during 52 weeks (Statista, 2020). So, they buy milk once roughly every two weeks. Thus, we selected seven days from today and 18 days to control milk purchasing behavior. Finally, 30 days from today was chosen to control for the most extended shelf-life that may be attributed to organic milk (i.e., if organic milk is ultra-pasteurized, then the average shelf-life would be 30-90 days when refrigerated). Finally, the menu of prices described in Table 3.2 was included.

Table 3.3: Attributes and levels used in the choice experiments.

Attributes	Levels
Milk type	Organic Conventional ¹
Label type	Static ¹ Smart
Additional information label	Ecolabel None ¹
Date printed on the container²	Tomorrow 7 days from today 18 days from today 30 days from today
Price (USD)	2.55, 3.28, 4.39, 5.31, 6.28, 7.20

¹Reference level in the data analysis.


²Variable set as numeric to determine the daily effect.

Each attribute was clearly explained before the beginning of the DCE questions (Figure 3.5). Respondents were also given a fourth opt-out option to choose none of the products presented. Each choice included five attributes and one level according to the experimental design. An example of the discrete choice experiment question is in Figure 3.3.

Figure 3.3: Discrete choice experiment sample question.

	Milk Option 1	Milk Option 2	Milk Option 3	Milk Option 4
Milk type	 Organic	 Conventional	 Organic	I wouldn't buy any of these
Date label type	 Scan me to find the predicted date.	static label mm/dd/yyyy	 Scan me to find the predicted date.	
Additional information label	 None	 Eco-certified	 None	
Date on label	Tomorrow	18 days from today	30 days from today	
Price	5.31	7.20	3.28	
	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	

Figure 3.4: Information treatment sample.








¿Did you know? 

In 2010, food loss and waste at the retail and consumer levels were 31% of the food supply, equaling 133 billion pounds and almost \$162 billion (USDA, 2010). Moreover, *one gallon of milk production added 5 kilograms of carbon dioxide (CO₂) to the air you breathe, the same as driving 12 miles in an average passenger car.*



By purchasing eco-certified milk, you can help reduce food waste.

Figure 3.5: Explanations of attributes and levels.

MILK TYPE		
	ORGANIC MILK	CONVENTIONAL MILK
DATE LABEL TYPE	<div style="border: 1px solid black; padding: 5px; width: fit-content; margin: 0 auto;"> static label mm/dd/yyyy </div> 	 
	STATIC LABEL	SMART LABEL
	A static label is printed on the container.	A smart label will collect up-to-date data from temperature sensors throughout the milk's supply chain to predict a more accurate date label.
ADDITIONAL INFORMATION LABEL		
	ECO-CERTIFIED	NONE
DATE ON LABEL	<p>It is the date you will see printed on a static label or embedded on a smart label. Assume you are buying TODAY, the printed/embedded date will be either Tomorrow, 7 days from today, 18 days from today, or 30 days from today.</p>	
PRICE	<p>The price YOU pay for ONE GALLON OF DAIRY MILK.</p>	

We used the Qualtrics Conjoint analysis package to design the experiment. Qualtrics' experimental design minimizes the number of profiles shown to the respondent while maximizing the data points and coverage (Qualtrics). The system designs the card sets based on the fractional factorial method (i.e., a fraction of the full factorial). Card sets are profiles (i.e., products, in this case, a gallon of dairy milk) based on the attributes and levels determined for the experiment (Qualtrics). The system uses a randomized, balanced design to determine the choice sets for each respondent. The algorithm used by Qualtrics ensures that card and choice sets are balanced. After defining the attributes and levels, 192 combinations were created. Based on these characteristics, 500 respondents were needed to provide sufficient statistical power for this design.

The third part of the survey aimed to ask respondents questions regarding their perceptions towards online behavior and Q.R. code use. This section also included a series of 5-point Likert questions in determining respondents' perceptions towards discarding behavior, food waste, labeling, and social currency (e.g., level of acceptance within a community, such as saving the planet, reducing food waste, etc.) The questions are based on the work of Richter & Bolkelman (2018). The list of questions regarding each perception is presented in Table 3.4. Finally, the fourth part of the survey asked respondents demographic questions regarding their age, children, education level, gender, income, marital status, ethnicity, size of the family, and state of residency.

Table 3.4. List of questions regarding consumers' perceptions.

Perceptions	Question	Variable
Discard behavior (when)	I discard milk on the date printed on the container.	“don”
	I discard milk when it passes the date printed on the container.	“daft”
	I usually discard milk before I am able to finish the whole container.	“dfin”
Discard behavior (sensory testing)	I smell milk before discarding it.	“dsmel”
	I taste milk before discarding it.	“dtast”
Food waste	How familiar are you with food waste issues related to fluid dairy milk?	
	I consider food waste when I make food choices.	“fcons”
	I feel bad when food is wasted.	“fbad”
	I feel it is wrong/morally reprehensible to waste food.	“fwron”
	I understand food waste is a significant issue in the U.S.	“fsig”
	I like to better handle food to help reduce food waste.	“fhand”
Labeling	I understand the printed date on milk indicates quality rather than food safety.	“daqua”
	I understand the differences between "sell by," "best if used by," and "use by" when printed on a container of milk.	“besel”
	I understand the difference between pasteurized and Ultra-Pasteurized (UP) milk.	“upmil”
Social currency	I like being part of online/in-person networks that promote sustainability awareness (i.e., environment, social, food waste).	“shsoc”
	I like sharing my social contributions on social media.	“promsu”

3.3 Survey data collection

A first draft of the questionnaire was sent to a team of experts in the Food Science and Technology Department at Cornell University, and their comments were used to revise the survey accordingly. After the Cornell’s Institutional Review Board for Human Participant Research approved the survey (Appendix 1. Institutional review board for human participants: Notice of exemption.), a beta version was tested with 50 respondents. The data was collected

through Prolific (Prolific, 2021) on January 12, 2021. We compensated each participant \$2.50 for a completed response, and we expected the survey to take 15 minutes to complete, for an effective compensation rate of \$10.00 per hour. In reality, the average response time was about eight minutes. There were three screening questions to allow respondents to take part in the survey:

- Respondents taking the survey or someone in their household should consume dairy milk.
- Respondents' country of residence should be the United States.
- Respondents should be at least 18 years old.

If any of these requirements were not met, respondents were asked to return the submission on Prolific, so an available spot was open again. After the pilot, some technical improvements were implemented.

The final version of the survey was released through Prolific on February 8, 2021. The same screening questions as those from the pilot were applied. We compensated each participant \$2.00 for a completed response, and we expected the survey to take 12 minutes to complete, for an effective compensation rate of \$10.00 per hour. In reality, the average response time was between seven and eight minutes. A total of 500 respondents completed the survey. Table 3.5 summarizes the demographic characteristics for the overall, control, and treatment groups. 62% of respondents are 35 years old or younger. Moreover, 56% of the sample are never married, and only 31% of the sample have children. Finally, gender is equally distributed.

There are some differences when comparing the sample demographic characteristics to the 2010 U.S. Census data. For instance, 62% of the sample are 35 years or younger compared to

33% in the Census). Moreover, 62% of people in our sample have never been married compared to 17.98% in the Census. Likewise, most of the U.S. population are high school graduates, whereas most people in our sample hold a bachelor's degree or have some college but not a degree. Finally, although our sample is biased toward younger and single people, the average household size is greater than that of the Census (i.e., 2.89 vs. 2.58). That suggests that our sample includes a larger proportion of single people living with roommates. Given the observed differences in our sample demographics relative to the U.S. population, we need to exercise caution when generalizing our results to the broader U.S. market.

Table 3.5: Demographic characteristics.

Variable	Overall, N=498¹	U.S. Census data³	Control, N=252¹	Treatment, N=246¹
Age				
25 or younger ²	118 (24%)	13.98%	65 (26%)	53 (22%)
26-35	189 (38%)	18.71%	87 (35%)	102 (42%)
36-45	89 (18%)	18.72%	47 (19%)	42 (17%)
46-55	56 (11%)	20.51%	31 (12%)	25 (10%)
56-65	29 (5.9%)	9.73%	9 (3.6%)	20 (8.2%)
65 or older	11 (2.2%)	18.35%	10 (4.0%)	1 (0.4%)
Gender				
Female ²	254 (52%)	50.80%	124 (50%)	130 (53%)
Male	230 (47%)	49.20%	122 (49%)	108 (44%)
Other	9 (1.8%)	-	4 (1.6%)	5 (2.1%)
Education				
Less than high school degree	4 (0.8%)	12.86%	3 (1.2%)	1 (0.4%)
High school graduate	49 (9.9%)	31.24%	21 (8.4%)	28 (12%)
Some college but no a degree	132 (27%)	16.84%	69 (28%)	63 (26%)
Associate degree in college (2-year) ²	44 (8.9%)	9.13%	22 (8.8%)	22 (9.1%)
Bachelor's degree in college (4-year)	183 (37%)	19.40%	95 (38%)	88 (36%)
Master's degree	62 (13%)	7.60%	32 (13%)	30 (12%)
Professional degree (JD, MD)	15 (3.0%)	1.54%	6 (2.4%)	9 (3.7%)
Doctoral degree	4 (0.8%)	1.39%	2 (0.8%)	2 (0.8%)

Marital status				
Divorced ²	35 (7.1%)	11.76%	22 (8.8%)	13 (5.4%)
Married	176 (36%)	60.56%	83 (33%)	93 (39%)
Never Married	272 (56%)	17.98%	141 (57%)	131 (54%)
Separated	5 (1.0%)	2.54%	2 (0.8%)	3 (1.2%)
Widowed	2 (0.4%)	7.16%	1 (0.4%)	1 (0.4%)
Children (Yes)	154 (31%)	48.4%	76 (31%)	78 (32%)
Household income				
Less than \$29,999	104 (21%)	21.11%	52 (21%)	52 (22%)
\$30,000 to \$59,999 ²	134 (28%)	23.17%	74 (30%)	60 (25%)
\$60,000 to \$89,999	105 (22%)	17.09%	44 (18%)	61 (25%)
Over \$90,000	143 (29%)	38.64%	76 (31%)	67 (28%)
Region				
Midwest ²	97 (20%)	17.15%	49 (20%)	48 (20%)
Northeast	111 (22%)	21.61%	53 (21%)	58 (24%)
South	201 (41%)	38.53%	102 (41%)	99 (41%)
West	85 (17%)	22.71%	46 (18%)	39 (16%)
Ethnicity				
White ²	381 (76%)	76.3%	194 (77%)	187 (76%)
Black or African American	43 (9%)	13.4%	20 (8%)	23 (9%)
American Indian or Alaska	4 (1%)	1.3%	2 (1%)	2 (1%)
Native				
Asian (including South Asian)	51 (10%)	5.9%	25 (10%)	26 (11%)
Hispanic/Latino	42 (8%)	18.5%	22 (9%)	20 (8%)
Other (please specify):	4 (1%)	3%	1 (0%)	3 (1%)
Household size	2.89 (1.31)	2.58	2.82 (1.38)	2.91 (1.27)

¹Mean (SD); n (%).

²Reference level for further analyses.

³U.S. Census Bureau (2010).

The data relating to behaviors collected in the first part of the survey are summarized in Table 3.6. Those results show that most people buy milk approximately once a week in large supermarkets (i.e., Walmart, Target, K-mart, etc.) and consume milk multiple times a week. Moreover, individuals in our sample primarily drink whole and reduced-fat milk and buy gallon and half-gallon milk bottles. Moreover, the more significant part of our sample has never consumed lactose-free milk, and 39% sometimes consume non-dairy milk. Of those respondents who consume non-dairy milk, 46% drink almond milk, followed by 19% of soymilk. Lastly,

43% of respondents said they consume non-dairy milk because of lactose intolerance, followed by 30% choosing longer product shelf life.

Behaviors regarding online buying frequency and use of Q.R. code show that 48% of respondents buy online a few times a month, followed by 27% a few times a week. In addition, 31% of respondents read food labels most of the time, and most people have never or probably not scanned (58%) a Q.R. code within food products. Finally, 45% of respondents are not familiar with food waste related to dairy milk.

Table 3.6: Behavioral characteristics.

Variable	Overall, N=498 ¹	Control, N=252 ¹	Treatment, N=246 ¹
Purchasing rate			
Less frequently than every 14 days	76 (15%)	36 (14%)	40 (16%)
Approximately every 10 - 14 days ²	175 (35%)	86 (34%)	89 (36%)
Approximately once a week	199 (40%)	107 (43%)	92 (37%)
Multiple times a week	42 (8.5%)	19 (7.6%)	23 (9.3%)
Daily	5 (1.0%)	3 (1.2%)	2 (0.8%)
Consumption rate			
Less than once a week ²	88 (18%)	47 (19%)	41 (17%)
Once a week	50 (10%)	23 (9.2%)	27 (11%)
Multiple times a week	209 (42%)	101 (40%)	108 (44%)
Once a day	91 (18%)	50 (20%)	41 (17%)
Multiple times a day	59 (12%)	30 (12%)	29 (12%)
Purchasing location			
Convenience stores ²	6 (1.2%)	3 (1.2%)	3 (1.2%)
Large supermarkets (Harps, Tops, Sprouts, etc.)	171 (34%)	78 (31%)	93 (38%)
Large/national big-box stores (Walmart, Target, K-Mart, etc.)	164 (33%)	85 (34%)	79 (32%)
Other	10 (2.0%)	8 (3.2%)	2 (0.8%)
Small/local grocery stores	76 (15%)	37 (15%)	39 (16%)
Specialty stores (Whole Foods, Trader Joe's, ethnic grocery stores, etc.)	32 (6.4%)	20 (7.9%)	12 (4.9%)
Warehouse club stores (Costco, Sam's Club, BJ's, etc.)	38 (7.6%)	21 (8.3%)	17 (6.9%)
Milk Fat content			
1% Low fat milk ²	66 (13%)	32 (13%)	34 (14%)
2% Reduced fat milk	193 (39%)	104 (41%)	89 (36%)

Other (please specify):	6 (1.2%)	4 (1.6%)	2 (0.8%)
Skim	42 (8.5%)	22 (8.8%)	20 (8.1%)
Whole milk	190 (38%)	89 (35%)	101 (41%)
Milk size			
Gallon ²	256 (52%)	135 (54%)	121 (49%)
Half-gallon	168 (34%)	77 (31%)	91 (37%)
More than one gallon	6 (1.2%)	4 (1.6%)	2 (0.8%)
Other (please specify):	1 (0.2%)	0 (0%)	1 (0.4%)
Quart	66 (13%)	35 (14%)	31 (13%)
Lactose free milk consumption			
Never	334 (67%)	163 (65%)	171 (70%)
Sometimes	99 (20%)	53 (21%)	46 (19%)
About half the time ²	14 (2.8%)	10 (4.0%)	4 (1.6%)
Most of the time	28 (5.6%)	15 (6.0%)	13 (5.3%)
Always	22 (4.4%)	11 (4.4%)	11 (4.5%)
Non-dairy milk consumption			
Never	180 (36%)	92 (37%)	88 (36%)
Sometimes	195 (39%)	99 (40%)	96 (39%)
About half the time ²	45 (9.1%)	26 (10%)	19 (7.7%)
Most of the time	40 (8.1%)	17 (6.8%)	23 (9.3%)
Always	36 (7.3%)	16 (6.4%)	20 (8.1%)
Non-dairy milk types			
Soy milk	100 (19%)	52 (19%)	48 (18%)
Almond milk	247 (46%)	124 (46%)	123 (46%)
Oat milk	98 (18%)	46 (17%)	52 (19%)
Coconut milk	77 (14%)	37 (14%)	40 (15%)
Vegan / Vegetarian diet or lifestyle	16 (3%)	10 (4%)	6 (2%)
Reasons to consume non-dairy			
Lactose intolerance	70 (43%)	40 (43%)	30 (43%)
Longer product shelf life	48 (30%)	27 (29%)	21 (30%)
Concerns about inflammation	22 (14%)	11 (12%)	11 (16%)
Concerns over antibiotics, pesticides, or hormones	22 (14%)	14 (15%)	8 (11%)
Online buying frequency			
Less than once per month	34 (6.9%)	19 (7.6%)	15 (6.1%)
About once a month	72 (15%)	36 (14%)	36 (15%)
A few times a month ²	237 (48%)	121 (48%)	116 (48%)
A few times a week	136 (27%)	69 (27%)	67 (27%)
About once a day	13 (2.6%)	4 (1.6%)	9 (3.7%)
Several times a day	3 (0.6%)	2 (0.8%)	1 (0.4%)
Reading food labels frequency			
Never	9 (1.8%)	4 (1.6%)	5 (2.1%)
Sometimes	139 (28%)	69 (27%)	70 (29%)
About half the time ²	89 (18%)	58 (23%)	31 (13%)
Most of the time	152 (31%)	64 (25%)	88 (36%)
Always	105 (21%)	56 (22%)	49 (20%)

Q.R. code use			
Definitely yes	77 (16%)	41 (16%)	36 (15%)
Probably yes	89 (18%)	50 (20%)	39 (16%)
Might or might not	44 (8.9%)	28 (11%)	16 (6.6%)
Probably not	107 (22%)	51 (20%)	56 (23%)
Definitely not ²	177 (36%)	81 (32%)	96 (40%)
Familiarity with food waste and milk			
Not familiar at all	222 (45%)	109 (44%)	113 (47%)
Slightly familiar	161 (33%)	80 (32%)	81 (33%)
Moderately familiar	78 (16%)	43 (17%)	35 (14%)
Very familiar	24 (4.9%)	15 (6.0%)	9 (3.7%)
Extremely familiar ²	8 (1.6%)	3 (1.2%)	5 (2.1%)

¹n (%)

²Reference level for further analyses.

Table 3.7 shows average perceptions for a list of statements regarding labeling, food waste, discard intentions, and social currency. The 5-point Likert scale asked respondents the extent to which they agreed with each statement from strongly disagree (1) to strongly agree (5). For example, when asked about discarding milk, the results suggest that most respondents agree with discarding milk before finishing the whole container. When asked about sensory evaluation when discarding milk, most respondents smell milk before discarding it. When asked about food waste issues, respondents mostly agree that understanding food waste is a significant issue in the U.S. and bad when wasting food. Finally, respondents seem to agree with considering food waste as wrong or morally reprehensible less.

When asked about labeling concerns, most respondents seem to agree with understanding the meaning of ‘sell by’, ‘best if used by’, and ‘use by’. However, they highly disagree with the printed date on milk signaling quality rather than safety. Finally, when asked about social currency behavior, they agree with online/in-person networks promoting sustainability.

Table 3.7: Perception's summary.

Perceptions	Variable	Overall ¹	Control ¹	Treatment ¹
Discard behavior (when)	I discard milk on the date printed on the container.	3.1554 (1.2789)	3.1885 (1.2295)	3.1224 (1.3280)
	I discard milk when it passes the date printed on the container.	3.1170 (1.1866)	3.0207 (1.1953)	3.2114 (1.1728)
	I usually discard milk before I am able to finish the whole container.	3.4656 (1.3830)	3.4530 (1.3948)	3.4779 (1.3739)
Discard behavior (sensory testing)	I smell milk before discarding it.	3.4077 (1.0187)	3.4112 (1.0466)	3.4043 (0.9927)
	I taste milk before discarding it.	3.0898 (1.3273)	3.0081 (1.3520)	3.1714 (1.3007)
Food waste	How familiar are you with food waste issues related to fluid dairy milk?	3.0171 (1.1699)	2.9871 (1.1465)	3.0470 (1.1946)
	I consider food waste when I make food choices.	3.4767 (0.9743)	3.5261 (0.9118)	3.4292 (1.0308)
	I feel bad when food is wasted.	2.8847 (1.1999)	2.8894 (1.1742)	2.8803 (1.2268)
	I feel it is wrong/morally reprehensible to waste food.	3.3832 (1.0404)	3.4306 (1.0183)	3.3378 (1.0614)
	I understand food waste is a significant issue in the U.S.	2.9699 (1.1524)	2.9780 (1.1345)	2.9623 (1.1715)
Labeling	I like to better handle food to help reduce food waste.	2.7037 (1.2413)	2.6198 (1.2273)	2.7869 (1.2520)
	I understand the printed date on milk indicates quality rather than food safety.	3.0729 (1.1317)	3.0693 (1.1012)	3.0765 (1.1632)
	I understand the differences between "sell by," "best if used by," and "use by" when printed on a container of milk.	3.112 (1.2723)	2.972 (1.2624)	3.252 (1.2692)
Social currency	I understand the difference between pasteurized and Ultra-Pasteurized (UP) milk.	3.7372 (1.4604)	3.5287 (1.5110)	3.9433 (1.3811)
	I like being part of online/in-person networks that promote sustainability awareness (i.e., environment, social, food waste).	2.9734 (1.5686)	2.8816 (1.5544)	3.0655 (1.5804)

¹Mean (std. dev)

4 EMPIRICAL METHODOLOGY

The empirical methodology is divided into four sections: (i) conditional logit model, (ii) mixed logit model, (iii) principal component analysis (PCA), and (iv) probit model.

The first two sections are discrete choice models. Choice models (CM) are economic tools usually applied to determine preferences and calculate willingness-to-pay (WTP). They are also valuable when considering multiple attributes. We used conditional and mixed logit models to characterize consumers' preferences and WTP for dairy milk attributes. The third section defines PCA as a data reduction tool for the perceptual data. Finally, the fourth section describes the model definition for the probit models created for the WTP for each attribute.

4.1 *Conditional logit model*

The conditional logit model describes how consumers choose among a discrete set of unordered outcomes. Its foundation is the concept of utility maximization. It is based on the assumption that there is some discrete set of choices that consumers can make. These choices are differentiated by a set of characteristics that consumers can rank according to their preferences. Thus, they derive utility from the collection of attributes and levels. This model is also established on the basic assumptions of consumer preference, which are transitivity, continuity, and non-satiation. The first assumption means that if an individual prefers product A to product B and product B to product C, then the individual also prefers product A to product C. The second assumption means that consumers' indifference curves slope downwards (i.e., it is assumed that consumers can substitute between available products). Finally, the third assumption states that an individual always prefers more to less, implying that utility functions increase (Varian, 1992).

The conditional logit model is determined by the random utility model (McFaden, 1986) under the assumption that the random part is independent and identically distributed (i.i.d.) extreme value (E.V.). Thus, the basic model is determined by the following equation:

$$\begin{aligned}
 U_{ijt} &= \beta_1 x_{1jt} + \beta_2 x_{2jt} + \dots + \beta_k x_{kjt} + \varepsilon_{ijt} \\
 &= V_{ijt} + \varepsilon_{ijt}, \forall j, \varepsilon_{ijt} \sim iid EV
 \end{aligned}
 \tag{3.2}$$

Where, $i = 1, \dots, I$ consumers ,

$j = 1, \dots, J$ choices,

$t = 1, \dots, T$ time

U_{ijt} = consumer i utility from choice j at time t ,

V_{ijt} = characteristic of choice j ,

β = preferences for observed characteristics,

ε_{ijt} = randomly distributed error term.

Based on equation 3.2, the probability for individual i choosing an alternative j over alternatives $1, \dots, J$ is

$$p_{ijt} = \text{prob}(j \text{ maximizes utility for } i \text{ at time } t) = \frac{\exp(V_{ijt}\beta)}{\sum_{j=1}^J \exp(V_{ijt}\beta)}
 \tag{3.3}$$

Three conditional logit models based on equation 3.2 were developed to analyze the data. Table 4.1 summarizes the variable specifications for each model:

1. CL1 presents each attribute's main effects.
2. CL2 adds interaction effects between each feature and the treatment group to CL1.

3. CL3 adds the interaction effect between the date label type and the additional information label to CL1.

Table 4.1: Variable specification for the models.

	CL1 (m=1)	CL2 (m=2)	CL3 (m=3)
Milk type	β_{11}	β_{12}	β_{13}
Date label type	β_{21}	β_{22}	β_{23}
Additional information label	β_{31}	β_{32}	β_{33}
Date on label	β_{41}	β_{42}	β_{43}
Price	β_{51}	β_{52}	β_{53}
Milk type * Treatment		γ_{12}	
Date label type * Treatment		γ_{22}	
Additional information label * Treatment		γ_{32}	
Date on label * Treatment		γ_{42}	
Date label type * Additional information label			α_{13}

Notes: β_{km} represents the mean effects for each variable, γ_{km} represents the interaction effects of each variable with the treatment group, and α_{km} represents the interaction effects between date label type and additional information label. k is the variable number. m is the model.

4.2 Mixed logit model

The mixed logit model allows preference parameters to differ for each respondent; thus, it captures unobserved heterogeneity. The formula to calculate the mixed logit model is from

Kalkbrenner et al. (2017):

$$U_{ijt} = \beta^0 Price_{ijt} + \sum_{k=1}^K \beta_i^k X_{ijt}^k + \varepsilon_{ijt} \quad (3.4)$$

$$\beta_i^k = \beta^k + \theta_i^k, \theta_i^k \sim N(0, \sigma_k^2), \quad (3.5)$$

From equation 3.4, the parameters to be estimated are β^0 and β_i^k where $k = 1 \dots K$ are product attributes with heterogeneous preferences. $Price_{ijt}$ represents the price, and X_{ijt}^k represents the k th non-price attribute of milk j at time t . ε_{ijt} represents the randomly distributed

error term. Price is set to be a fixed parameter (Hole, 2007), and all the other variables are set to be randomized and normally distributed when calculating the mean effects.

Based on equation 3.4, and assuming that ε_{ijt} is independently and identically distributed extreme value type 1, the probability for individual i choosing an alternative (milk) j over choices $1, \dots, J$ over time t is,

$$p_{ijt} = \int \dots \int \frac{\exp(\beta^0 Price_{ijt} + \sum_{k=1}^K \beta_i^k X_{ijt}^k)}{\sum_{j=1}^J \exp(\beta^0 Price_{ijt} + \sum_{k=1}^K \beta_i^k X_{ijt}^k)} dF(\theta_i^1) \dots dF(\theta_i^K) \quad (3.6)$$

In equation 3.6, $F(\cdot)$ represents the cumulative standard normal distribution and θ_i^K “are normally distributed terms designed to account for any unobserved heterogeneity in the marginal utility” (Kalkbrenner et al., 2017).

Three models were also created based on equation 3.4. The specifications for each model are as follows:

1. MIXL1 shows the main effects when the price coefficient is constant and all the other variables are randomized.
2. MIXL2 adds interaction effects between each feature and the treatment group to MIXL1.
3. MIXL3 presents the interaction effect between date label type and the additional information label to MIXL1.

We also created interaction variables between the demographic, behavioral, and perceptual data to assess consumers’ heterogeneity. The proposed model continually added those interaction variables to MIXL1.

4.2.1 Individual parameters

We estimate the expected value of a random coefficient ($E(\beta)$) using the mean of the R draws (Croissant, 2020). The distribution of the R draws is $\bar{\beta} = \sum_{r=1}^R \beta_r$. First, the probabilities of the observed choice of i for every value of β_r are calculated by:

$$p_{irt} = \frac{\sum_{j=1}^J \gamma_{ijt} \exp(\beta_r' X_{ijt})}{\sum_{j=1}^J \exp(\beta_r' X_{ijt})}, \quad (3.7)$$

γ_{ijt} represents a dummy variable equal to one if i has chosen alternative j at time t . Then, the expected value of the parameter for each person is calculated based on the probabilities from equation 3.7 to weight the β values (Croissant, 2020):

$$\hat{\beta}_i = \frac{\sum_r p_{irt} \beta_r}{\sum_r p_{irt}} \quad (3.8)$$

4.2.2 Willingness-to-pay (WTP)

The WTP for a level within an attribute (e.g., organic, ecolabel present) is the increase in the purchase price that keeps the customers' utility constant. The WTP is calculated by keeping the price constant and applying equation 3.9.

$$WTP = -\frac{\beta_i^k}{\beta^0} \quad (3.9)$$

4.3 Principal component analysis (PCA)

PCA is a data reduction method that aims to decrease the dimension of the data by keeping as much variability as possible (Johnson et al., 2019). It is a statistical method that evaluates the correlation matrices of eigenvalues and eigenvectors to determine linear combinations of p variables from large datasets (Bei, et al., 2012). The eigenvalues constitute a measure of the

amount of the original total variance explained by each new derived variable (i.e., the sum of the eigenvalues is the total variation of the dataset) (Johnson et al., 2019). The eigenvectors of the matrix are the weights used to determine the principal components. The loadings are interpreted as the higher the loading, the more important is the variable to construct the component (Johnson et al., 2019).

More specifically, it conveys the correlation between a “correlated number of p variables and an uncorrelated number of k variables” (Bei, et al., 2012). Some benefits of this methodology are that it allows to better visualize the weights and directions of each new linear combination through biplots (i.e., the configuration of data in multidimensional space) (Bei, et al., 2012). Moreover, it is a widely used method to rescale raw data. Thus, the comparability of data across individuals increases (Chapman, et al., 2015). Finally, we used PCA to reduce the data points for the perceptual questions.

4.4 Probit model

We developed five probit models to explore consumers’ heterogeneity. First, we calculated the WTP per respondent per attribute based on the results from MIXL 1. Then, we determined four models that corresponded to individual WTP for milk type, additional information label, the date on the label, and date label type. For these models, we set V_i as a binary variable such that $V_i=1$ if individual WTP > mean; otherwise, $V_i=0$. The model

$$V_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \varepsilon_i \quad (3.10)$$

with

$$P(V_i = 1 | x_1, x_2, \dots, x_k) = \Phi(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k) \quad (3.11)$$

is the population probit model with multiple regressors x_1, x_2, \dots, x_k and $\Phi(\cdot)$ is the cumulative standard normal distribution function (Econometrics with R).

Our model sets x_1, x_2, \dots, x_k as the demographic, behavioral, and perceptual variables (Table 4.2). β_0 is the intercept, β_1 is the coefficient estimate for each regressor variable, and ε_i is the error term.

We also developed a fifth model based on equation 3.10 for the WTP for date label type, where we set V_i as a binary variable such that if individual WTP > 0, then $V_i = 1$; otherwise, $V_i = 0$.

Table 4.2: Specification of variables for the probit model.

Variable	Class	Levels	Specification
Age	Categorical	Based on Table 3.5.	χ_1
Children	Categorical	Based on Table 3.5.	χ_2
Education level	Categorical	Based on Table 3.5.	χ_3
Gender	Categorical	Based on Table 3.5.	χ_4
Income	Categorical	Based on Table 3.5.	χ_5
Marital status	Categorical	Based on Table 3.5.	χ_6
Ethnicity	Categorical	Based on Table 3.5.	χ_7
Size of the family	Numerical	Based on Table 3.5.	χ_8
Region	Categorical	Based on Table 3.5.	χ_9
Milk Fat content	Categorical	Based on Table 3.6.	χ_{10}
Lactose-free	Numerical	Always (5) to never (1)	χ_{11}
Location of purchase	Categorical	Based on Table 3.5.	χ_{12}
Non-dairy milk consumption	Numerical	Always (5) to never (1)	χ_{13}
Purchasing rate	Numerical	Daily (5) to less than every 14 days (1)	χ_{14}
Milk bottle size	Categorical	Based on Table 3.5.	χ_{15}
Food waste familiarity	Numerical	Extremely familiar (5) to no familiar at all (1)	χ_{16}
Online buying behavior	Numerical	Several times a day (5) to less than once per month (1)	χ_{17}
Q.R. code use	Numerical	Definitely yes (5) to definitely no (1)	χ_{18}
Discarding (when)	Categorical	1 if positive, 0 if negative	χ_{19}
Discarding (sensory analysis)	Categorical	1 if positive, 0 if negative	χ_{20}
Food waste	Categorical	1 if positive, 0 if negative	χ_{21}
Labelling	Categorical	1 if positive, 0 if negative	χ_{22}
Social currency	Categorical	1 if positive, 0 if negative	χ_{23}
WTP milk type	Categorical	1 if over the mean, 0 if less than the mean	v_1
WTP additional information	Categorical	1 if over the mean, 0 if less	v_2

label		<i>than the mean</i>	
WTP date on label	<i>Categorical</i>	<i>1 if over the mean, 0 if less than the mean</i>	v_3
WTP date label type ₁	<i>Categorical</i>	<i>1 if over the mean, 0 if less than the mean</i>	v_4
WTP date label type ₂	<i>Categorical</i>	<i>1 if positive, 0 if negative</i>	v_5

5 RESULTS

The results section starts by presenting the distribution of levels seen and chosen by the respondents. We then introduce the findings for the conditional and mixed logit models, followed by the results for the probit model. The *gmn* package from R was used to run the discrete choice models and WTP (Daziano R, 2017).

5.1 *Distribution of levels seen and chosen*

Table 5.1 summarizes the distribution of levels seen by the respondents and the proportion of levels chosen. Based on that information, the experimental design appears well-balanced. Moreover, the variables show significant heterogeneity in preferences, except the date on the label. For that variable, most respondents chose the options with the most extended shelf-life.

Table 5.1: Distribution of levels seen and chosen.

	Overall		Control		Treatment	
	Seen (%)	Chosen ¹ (%)	Seen (%)	Chosen ¹ (%)	Seen (%)	Chosen ¹ (%)
Price (in\$)						
2.55	17.11	58.10	8.69	57.41	8.42	58.81
3.28	16.99	51.79	8.49	52.42	8.49	51.16
4.39	16.65	36.52	8.42	36.94	8.23	36.09
5.31	16.67	24.68	8.44	24.79	8.23	24.57
6.28	16.24	17.62	8.15	16.45	8.08	18.81
7.20	16.34	9.41	8.17	9.85	8.17	8.97
Milk type						
Conventional	49.82	30.83	25.14	32.86	24.68	28.77
Organic	50.18	35.82	25.23	33.81	24.95	37.85
Date label type						
Static	43.20	38.91	43.00	39.14	43.42	38.67
Smart	56.80	29.09	57.01	28.95	56.58	29.24
Additional information label						
None	49.77	29.18	50.00	30.47	49.55	27.85
Ecolabel	50.23	37.45	50.00	36.20	50.45	38.71
Date on label						
Tomorrow	14.06	11.83	7.22	11.63	6.83	12.04
7 days from tomorrow	28.33	28.66	14.38	27.74	13.95	29.62
18 days from tomorrow	28.67	40.49	14.56	42.26	14.11	38.66
30 days from tomorrow	28.95	41.26	14.22	40.88	14.74	41.63

¹It is the percentage from the total seen of each level. For instance, from the 17.11% who saw \$2.55, 58.10% selected that option.

5.2 Conditional logit model

Table 5.2 summarizes the results from the conditional logit models. As detailed in Table 3.3, conventional milk, static label, and no additional information label were set as reference

levels for this analysis. Date printed on the container and price were coded as continuous variables. Each coefficient represents the utility of each level in the choice experiment.

All parameters are highly significant for CL1 at the 0.1% level. As expected, the price has a negative coefficient, which implies downward-sloping demand curves (i.e., customers prefer lower prices). On the other hand, milk type, additional information label, and date on the label have positive coefficients. Therefore, organic milk, an eco-certified label, and extended shelf-life increase the likelihood of buying a milk bottle under experimental conditions. In other words, shoppers prefer organic over conventional milk, as found by Hasselbach & Roosen (2015) and Scozzafava et al. (2020). Similarly, shoppers prefer an ecolabel over none, which supports H₃.

Likewise, their perceived utility increases with extended shelf life, which provides support for H₁. This finding is in line with Li et al. (2020), who determined that shelf-life influences perceived products' freshness (i.e., a value driver).

Surprisingly, the smart label has a negative coefficient. Thus, a smart label decreases the likelihood of buying a milk bottle under the experiment conditions. Namely, shoppers prefer a static label over a smart label. This finding does not support H₂. Furthermore, it is contrary to the results found by Yin et al., 2020 where the WTP increases in the presence of an organic and traceable product.

The sign of the coefficients for CL2 remained the same as those from CL1. However, the coefficients' magnitude and statistical significance varied. The main effect for organic milk is no longer statistically significantly different from zero at conventional levels. However, the information card does moderate the impact of organic milk at a magnitude like the main effect

result in CL1. This implies that the information treatment is driving the positive preference for organic milk. Some explanations for this result are that consumers' preference (i.e., and WTP) for organic compared to conventional milk increases when presenting information regarding animal welfare and environmental sustainability (Scozzafava et al., 2020).

The information card positively moderates the impact of the additional information label, implying a greater perceived preference for the ecolabel in the presence of a cognitive and attention nudge. Moreover, the total utility for the ecolabel is 0.639 ($\beta_{32} + \gamma_{32} = 0.2836 + 0.3554$), which is higher than that from CL1 ($\beta_{31} = 0.4569$). These results support H₃. On the other hand, the information card does not moderate the date label type and date on the label's effect. The main effect for the smart label remained the same, and there is no statistically significant additional effect for the treatment group. Finally, the main impact for extended shelf life increased slightly, and the point estimate for the interaction effect is negative, but it is not statistically significant.

The main effects in CL3 remained the same as those from CL1. Moreover, CL3 shows that the complementary relationship between the smart label and the ecolabel is not statistically significant.

These results are interesting and provide a straightforward analysis of the average effects in our sample. However, the conditional logit fails to capture preference heterogeneity across respondents, and Table 3.4 suggests this may be an important factor to analyze.

Table 5.2: Conditional logit parameter estimates.

	CL1 ¹	CL2 ¹	CL3 ¹
Milk type	0.2834 (0.065)***	0.1414 (0.091)	0.2833 (0.0654)***
Date label type	-0.4045 (0.066)***	-0.394 (0.093)***	-0.3608 (0.0977)***
Additional information label	0.4569 (0.05)***	0.2836 (0.090)**	0.5013 (0.0981)***
Date on label	0.0444 (0.003)***	0.0480 (0.005)***	0.0443 (0.0033)***
Price	-0.6082 (0.024)***	-0.6114 (0.025)***	-0.6085 (0.0244)***
Milk type * Treatment		0.2809 (0.1309)*	
Date label type * Treatment		-0.0137 (0.1320)	
Additional information label * Treatment		0.3554 (0.1308)**	
Date on label * Treatment		-0.0072 (0.0064)	
Date label type * Additional information label			-0.082 (0.1349)
Log-Likelihood	-1,484.4	-1477.5	-1,484.2
N(respondents) ²	498	498	498
N (choice sets)	1,864	1,864	1,864
N (alternatives)	5,592	5,592	5,592

Notes: .p<0.1, *p<0.05, **p<0.01, ***p<0.001

¹Mean (Std. Err.)

²Two data points were dropped as the DCE selection for the four questions was the opt-out option.

5.3 Mixed logit model

Table 5.3 summarizes the results for the mixed logit models. As with the conditional logit models, the coefficients correspond to the utility for each attribute. The standard deviations account for the heterogeneity captured by the mixed logit model; thus, if the standard deviation for a feature is statistically significant, the preference for that attribute varies to a certain degree (Carlsson et al., 2003). As expected, the coefficient for the price is negative, which implies that customers prefer to pay less for milk. This effect is constant among the three models.

MIXL1 shows the main effects when the price is set constant, and all the other variables are allowed to vary randomly. The mean and standard deviation estimates for the main effects for

all levels are highly significant at a 0.1% level. Overall, coefficients' signs for each level are the same as those for the conditional logit model; however, the magnitudes of the coefficient estimates increase. Thus, the utility for organic compared to conventional milk, an ecolabel compared to none, and extended shelf-life increases. On the other hand, the negative preferences for price and a smart label are also stronger.

MIXL2 shows the main effects when the price is set constant and all the other variables are randomized. In addition, MIXL2 adds interaction effects with the treatment group. The utility for organic milk for both the main and interaction effects is not statistically significant. However, the absolute magnitude of the negative preference for an intelligent label increases. The interaction effect between treatment and a smart label attenuates the negative main effect, but the coefficient estimate is not statistically significant. One interesting finding is that the preference for the eco-certified label increases in the presence of the information treatment, which implies that customers in the treated group are willing to pay an additional premium over the main effect. The results obtained for the main effect of extended shelf life are like those obtained for the conditional logit model. These results again support H_3 and H_1 but weaken H_2 .

MIXL3 shows the main effects when the price is set constant, all the other variables are randomized, and an interaction effect is included between the smart label and ecolabel attributes. The main effects remain steady; however, the estimated effect of the interaction between both features is not statistically significant.

Given that the standard deviations for milk type, date label type, and additional information label are highly statistically significant, this indicates substantial preference heterogeneity among customers. Individual parameters may explain that heterogeneity (e.g., age, income, behaviors, etc.). Although the standard deviation for the date on the label is statistically

significant, the magnitude of the coefficient may imply that heterogeneity is not economically meaningful.

Table 5.3: Mixed logit parameter estimates.

	MIXL1 ¹	MIXL2 ¹	MIXL3 ¹
Mean estimates			
Milk type	0.4025 (0.1086)***	0.2323 (0.1498)	0.4026 (0.1085)***
Date label type	-0.5410 (0.1012)***	-0.5742 (0.1418)***	-0.4859 (0.1373)***
Additional information label	0.5899 (0.1018)***	0.3327 (0.1385)*	0.6449 (0.1387)***
Date on label	0.0622 (0.0057)***	0.0661 (0.0076)***	0.0623 (0.0057)***
Price	-0.8077 (0.0434)***	-0.8109 (0.0436)***	-0.8074 (0.0433)***
Milk type * Treatment		0.3397 (0.2130)	
Date label type * Treatment		0.0752 (0.1984)	
Additional information label * Treatment		0.5335 (0.2015)**	
Date on label * Treatment		-0.0077 (0.0098)	
Date label type * Additional information label			-0.0988 (0.1724)
Standard deviation estimates			
Milk type	1.3577 (0.1720)***	1.3324 (0.1726)***	1.3559 (0.1718)***
Date label type	1.0376 (0.1677)***	1.0511 (0.1675)***	1.0406 (0.1677)***
Additional information label	1.1074 (0.1770)***	1.1006 (0.1772)***	1.1064 (0.1772)***
Date on label	0.0530 (0.008)***	0.0532 (0.0082)***	0.0529 (0.0082)***
Log-Likelihood	-1,438.9	-1,433.5	-1,438.7
N(respondents) ²	498	498	498
N (choice sets)	1,864	1,864	1,864
N (alternatives)	5,592	5,592	5,592

Notes: .p<0.1, *p<0.05, **p<0.01, ***p<0.001

¹Mean (Std. Err.)

²Two data points were dropped as the DCE selection for the four questions was the opt-out option.

5.4 Willingness-to-pay (WTP)

Table 5.4 shows the attribute-level willingness-to-pay estimates for each model based on the mixed logit model. Again, all parameters exhibit the same significance as those from the mixed logit model. Consequently, all parameters are significant for MIXL1. From the results on MIXL1, the WTP premium for organic compared to conventional milk is \$0.50. The price premium for the ecolabel compared to none is \$0.73, and the price premium for an extra day of shelf-life is \$0.08. On the other hand, consumers are willing to pay \$0.67 *less* for a smart label over a static label.

When analyzing the results from MIXL2, the main and interaction effects for the WTP for organic milk compared to conventional milk are not statistically significant. One interesting finding is that the willingness to pay for the eco-certified product increases in the presence of the information treatment. Thus, the WTP for the eco-certified product rises by \$0.66 (interaction effect) over the \$0.41 (main effect) for treated individuals. These results imply that a product's preference to decrease food waste is significantly higher when customers are given cognitive and attention information.

When analyzing the results from MIXL3, the WTP for the interaction between the smart and ecolabel is not statistically significant. Thus, these results again support H₃ and H₁ but weaken H₂.

Table 5.4: Willingness-to-pay estimates (in USD)

	MIXL1	MIXL2	MIXL3
Milk type	0.4983***	0.2865	0.4986***
Date label type	-0.6699***	-0.7081***	-0.6017***
Additional information label	0.7304***	0.4103*	0.7987***
Date on label	0.0771***	0.0814***	0.0771***
Milk type * Treatment		0.4189	
Date label type * Treatment		0.0928	
Additional information label * Treatment		0.6578**	
Date on label * Treatment		-0.0094	
Date label type * Additional information label			-0.1224

Notes: .p<0.1, *p<0.05, **p<0.01, ***p<0.001

5.5 CHARACTERIZING HETEROGENEITY

To characterize heterogeneity, we added interaction effects between the demographic, behavioral, and perceptual data. We also estimate probit models that assess the likelihood that the WTP for each attribute was greater than the mean. Additionally, given that the mean WTP for date label type is negative, we estimate a probit model to assess the probability that WTP for date label type is positive.

5.5.1 PCA results

Principal component analysis with Stata/IC 16.1 was developed to reduce the number of variables related to consumer's perceptions. Table 5.5 summarizes the main results. Components with an eigenvalue less than one are dropped from the analysis, and a varimax rotation was applied. The significant loadings are those with loading greater than 0.40 in absolute value (Qi & Roe, 2016).

Table 5.5. Principal component analysis summary.

	Rotation	Variance	Proportion of variance	Cumulative proportion
Discarding				
When		1.51667	0.3033	0.3033
“daft”	0.6465			
“don”	0.6666			
“dfin”	0.3663			
Sensory		1.21548	0.2431	0.5464
“dsmel”	0.7169			
“dtast”	0.6600			
Food waste				
		2.39184	0.4784	0.4784
“fsig”	0.3979			
“fbad”	0.4425			
“fwron”	0.4242			
“fcons”	0.4489			
“fhand”	0.5142			
Labeling				
		1.40568	0.4686	0.4686
“upmil”	0.4536			
“daqua”	0.6654			
“besel”	0.5928			
Social currency				
		1.42819	0.7141	0.7141
“shsoc”	0.7071			
“promsu”	0.7071			

5.5.2 Interaction effects with demographics, behaviors, and perceptions.

We created interaction terms between each attribute and demographic, behavioral, and perceptual data points to explore if those variables moderate the impact of each variable when choosing a milk bottle. Those interactions terms were continually added to MIXL1. Table 5.6 presents a summary of variables for which the interaction coefficient estimates are statistically significant at $p < 0.05$. Overall, the following variables have no statistical significance at any

conventional level with any alternative variable: marital status, region, ethnicity, milk fat content, milk size, household size, labeling, and discard perceptions.

5.5.2.1 Milk type

The interaction effects with a positive and statistically significant coefficient for organic compared to conventional milk are buying at warehouse club stores, specialty stores and consuming lactose-free milk always or most of the time. On the other hand, the interaction effects with a negative and statistically significant coefficient regarding organic compared to conventional milk are being 56 years or older, making less than \$29,999; purchasing milk approximately once a week, consuming milk once a day, never consuming non-dairy milk, and buying online about once a month.

5.5.2.2 Date label type

The interaction effects with a positive and statistically significant coefficient regarding a smart label compared to a static label are buying online several times a day and probably not using a Q.R. code compared to definitely not using a Q.R. code. This result is counterintuitive, and a part of it may be explained by consumers being curious about using the technology for the first time. On the other hand, the interaction effects with a negative and statistically significant coefficient regarding a smart label compared to a static label are all purchase locations compared to convenience stores.

5.5.2.3 Additional information label

The interaction effects with a positive and statistically significant coefficient regarding an ecolabel compared to none are food waste perceptions, always consuming non-dairy milk, buying online about once a day, reading food labels always or most of the time, and definitely using a Q.R. code. On the other hand, the interaction effects with a negative and statistically

significant coefficient regarding an ecolabel compared to none are 46 to 55 or 65 years or older, men compared to women, purchasing milk multiple times a week, and consuming milk numerous times a day.

5.5.2.4 Date on label

The interaction effects with a positive and statistically significant coefficient towards extended shelf-life are consuming lactose-free milk most of the time, sometimes consuming non-dairy alternatives, social currency, and food waste. On the other hand, the interaction effects with a negative coefficient and statistically significant towards extended shelf-life are having a high school level of education and purchasing milk approximately once a week.

Table 5.6: Interaction effects with demographics, behaviors, and perceptions.

Variable	Interaction	Milk type	Date label type	Additional information label	Date on label
Age	25 or younger ¹				
	46 – 55			(-)	
	56 – 65	(-)			
	65 or older	(-)		(-)	
Gender	Female ¹				
	Male			(-)	
	Other			(-)	
Education	Associate degree in college (2-year) ¹				
	High school				(-)
Household income	\$30,000 to \$59,999 ¹				
	Less than \$29,999	(-)			
Purchasing rate	Approximately every 10 - 14 days ¹				
	Approximately once a week	(-)			(-)
	Multiple times a week			(-)	
Consumption rate	Less than once a week ¹				
	Multiple times a day			(-)	

Variable	Interaction	Milk type	Date label type	Additional information label	Date on label
	Once a day	(-)			
Purchasing location	Convenience stores ¹				
	Large supermarkets (Harps, Tops, Sprouts, etc.)		(-)		
	Large/national big-box stores (Walmart, Target, K-Mart, etc.)		(-)		
	Small/local grocery stores		(-)		
	Specialty stores (Whole Foods, Trader Joe's, ethnic grocery stores, etc.)	(+)			
	Warehouse club stores (Costco)	(+)	(-)		
Lactose free milk consumption	About half the time ¹				
	Always	(+)			
	Most of the time	(+)			(+)
Non-dairy milk consumption	About half the time ¹				
	Always			(+)	
	Never	(-)			
	Sometimes				(+)
Online buying frequency	A few times a month ¹				
	About once a day			(+)	
	About once a month	(-)			
	Several times a day		(+)		
Reading food labels frequency	About half the time ¹				
	Always			(+)	
	Most of the time			(+)	
Q.R. code use	Definitely not ¹				
	Definitely yes			(+)	
	Probably not		(+)		
	Probably yes			(+)	
Perceptions	Food waste			(+)	(+)
	Social currency				(+)

Notes: (+) and (-) identify the interactions effects that are positive/negative (respectively) and statistically significant with $p < 0.05$

¹Reference level.

5.5.3 *Exploratory analysis of WTP for each attribute*

We also developed a probit model to further explore heterogeneity. Table 5.7 summarizes the average marginal effects of each variable that was statistically significant at $p < 0.05$. The variables that had no statistically significant marginal effects were food waste, discard (sensory testing), familiarity with food waste, household size, online buying frequency, and milk type.

The variables that increase the likelihood of WTP for an ecolabel to be over the mean are being 46-55 years old and 65 or older, having any level of education compared to an associate degree in college, reading food labels frequently, and using Q.R. codes. On the other hand, the variables that decrease the likelihood of WTP for an ecolabel to be over the mean are the consumption rate and all purchase locations compared to convenience stores.

The likelihood of WTP for organic milk to be over the mean is positively impacted by being between 36 and 65 years old, active on social media, and consuming non-dairy milk. However, the likelihood of the WTP for organic milk is negatively impacted by gender (male) and purchasing rate.

The likelihood of WTP for extended shelf-life to be over the mean is positively impacted by being between 26-35 years old, having a positive perception towards labeling (i.e., it implies knowing the difference between pasteurized and UP milk and understanding the meaning of date labels), being active on social media, buying more than one gallon of milk or a quart milk bottle, and living in the Southern region of the U.S.

The likelihood of WTP for date label type to be over the mean is positively impacted by holding a professional degree, consuming lactose-free milk, and having a higher perception of labeling. Conversely, the variables that decrease the likelihood of WTP for a smart label to be

over the mean are education (i.e., doctoral and less than high school compared to an associate degree in college), all purchase locations compared to convenience stores, and discard perceptions.

Finally, we also estimate a probit model to determine which variables impact the likelihood of choosing a smart over a static label (i.e., individual WTP > 0). The results show that having an income between \$60,000 and \$89,000, consuming lactose-free milk, and being from the Southern region of the U.S. would increase the likelihood of choosing an intelligent label. Whereas holding a doctoral degree compared to an associate degree and all purchase locations compared to convenience stores would decrease the possibility of using a smart tag.

Table 5.7: Average marginal effects for probit regression models.

Variable	individual WTP > mean WTP				individual WTP > 0
	Additional information label	Milk type	Date on label	Date label type (mean)	Date label type (positive)
Age	25 or younger ¹				
	26 – 35		(+)		
	36 – 45		(+)		
	46 – 55	(+)	(+)		
	56 – 65		(+)		
	65 or older	(+)			
Gender	Female ¹				
	Male	(-)	(-)		
Education	Associate degree ¹				
	Bachelor (4 yrs.)	(+)			
	Doctoral	(+)		(-)	(-)
	High school	(+)			
	Less than high school			(-)	
	Master's	(+)			

Variable	individual WTP > mean WTP				individual WTP > 0
	Additional information label	Milk type	Date on label	Date label type (mean)	Date label type (positive)
Professional	(+)			(+)	
Household income	\$30,000 to \$59,999 ¹ \$60,000 to \$89,999				(+)
Purchasing rate		(-)			
Consumption rate	(-)				
Purchasing location	Convenience stores ¹				
	Large supermarkets (Harps, Tops, Sprouts, etc.)	(-)		(-)	(-)
	Large/national big-box stores (Walmart, Target, K-Mart, etc.)	(-)		(-)	(-)
	Other				
	Small/local grocery stores	(-)		(-)	(-)
	Specialty stores (Whole Foods, Trader Joe's, ethnic grocery stores, etc.)			(-)	(-)
	Warehouse club stores (Costco, Sam's Club, BJ's, etc.)	(-)		(-)	(-)
Lactose-free milk consumption				(+)	(+)
Non-dairy milk consumption		(+)			
Reading food labels frequency	(+)				
Q.R. code use	(+)				
Perceptions	Labeling		(+)	(+)	
	Food waste				
	Social currency	(+)	(+)		
	Discard: when Discard: sensory testing			(-)	
Milk size	Gallon ¹				
	More than one gallon		(+)		
	Quart		(+)		

Variable	individual WTP > mean WTP				individual WTP > 0
	Additional information label	Milk type	Date on label	Date label type (mean)	Date label type (positive)
Region	Midwest ¹				
	South		(+)		(+)
Num. obs. ²	479	479	479	479	479
Log Likelihood	-296.9955	-	-	-300.4037	-161.8085
Deviance	596.9909	578.9749	600.5919	600.8074	323.6170
AIC	693.9909	678.9749	700.5919	700.8074	423.6170
BIC	902.5759	887.5599	909.1769	909.3924	632.2020

Notes: (+) and (-) identify the interactions effects that are positive/negative (respectively) and statistically significant with $p < 0.05$

¹Reference level.

²Twenty-one observations were dropped due to missing values for some variables.

6 CONCLUSIONS

This thesis aimed to analyze the impact of shelf-life, quality disclosure, and ecolabels on perceived value in the food and beverage markets. We focus on dairy milk because of its relevance within the healthy American diet and its impact on food waste. Understanding consumer preferences and willingness-to-pay is crucial for stakeholders within the food supply chain who aim to implement technology to extend shelf-life, and thus, reduce food waste (Yu & Jaenicke, 2021). We collected primary data of 500 respondents-split into control and treatment (i.e., respondents in the treatment group saw an information card explaining the ecolabel and showing facts about food waste within the milk industry) groups in February 2021. We implemented a discrete choice experiment to test the impact of date label type (i.e., a smart label compared to a static label), the date on the label (i.e., tomorrow, seven days from today, 18 days from today, and 30 days from today), additional information label (i.e., ecolabel compared to none), milk type (i.e., organic compared to conventional), and price.

Our first hypothesis (H_1) was that consumers are willing to pay more for milk with longer shelf life, *ceteris paribus*, which aims to assess shelf-life value. The results of the conditional and mixed logit models supported this hypothesis as consumers showed a positive preference towards extending milk's durability. The estimated WTP for an extra day of shelf-life is \$0.08. This result agrees with the existing literature regarding the importance of shelf-life as a value driver for consumers and retailers (ReFED, 2021; Roe et al., 2018; Theotokis et al., 2012; Wu et al., 2017). Furthermore, extended shelf-life may represent a convenience factor to consumers as it decreases the number of trips to the store and it helps reduce food waste (Yu & Jaenicke, 2021). In addition, retailers benefit from extended shelf-life by maximizing their profits and optimizing inventory (Wu et al., 2017). Based on these results, we fail to reject H_1 .

Our second hypothesis (H_2) was that consumers are willing to pay more for milk with precise spoilage information, *ceteris paribus*, which aims to assess the value of quality disclosure. We used the attribute date label type to test consumers' preference towards a smart label (i.e., collecting up-to-date data from temperature sensors throughout the milk's supply chain to predict a more accurate date label). We find that consumers have a negative preference towards a smart label, which implies they prefer a static tag. Thus, shoppers are willing to pay \$0.67 less over a static label, which means they would need to receive an incentive valued at \$0.67 to use the smart product. This result contradicts Yin et al. (2020), who found that the WTP increases for an organic and traceable product. Indeed, they analyzed shrimp in China, where a food safety outbreak related to this product occurred. That may increase people's acceptability towards traceability (Yin et al., 2020). Based on these results, we reject H_2 .

Our third hypothesis was that consumers are willing to pay more for milk with a food waste-related ecolabel, *ceteris paribus*, which aims to assess the value of an eco-certified label. We specify the attribute additional information label to determine the preference for an ecolabel compared to none. We also implemented a treatment group to determine the preference change when shown a cognitive nudge with information related to food waste. The WTP for the overall sample is \$0.73. The WTP for the ecolabel in the treatment group is \$1.07 (i.e., \$0.4103 from the main effect plus \$0.66 from the interaction effect). This result can partly be explained by the recent consumers' preference towards purpose-driven (i.e., consumers that buy services and products aligned with their lifestyles and values) (Haller et al., 2020). Moreover, purpose-driven consumers are willing to adjust their buying behaviors to diminish the environmental impact and promote sustainable practices (Haller et al., 2020). Based on these results, we fail to reject H_3 .

As seen in the literature and the present thesis, consumers favor milk with extended shelf-life. However, shoppers have an aversion towards using the Q.R. code (i.e., smart tag). Several reasons may explain this situation. First, the benefits of getting the more precise date label are outweighed by the extra effort of getting that information. For instance, scanning the milk bottle to get an accurate date may be burdensome because it implies adding an extra step to their shopping routine. Moreover, they would require a smartphone to access the embedded date or a specific application to read the Q.R. code, which may be a barrier for some consumers.

Some other findings include that shoppers' preference towards price is negative across all respondents, which means they prefer lower prices. In addition, the exploratory analysis allows us to examine some factors that may influence the likelihood of shoppers towards the preference for each attribute. Finally, the fact that the WTP for organic milk compared to conventional milk in the treatment group was not statistically significant may imply a substitution effect wherein the ecolabel is perceived as more valuable to the consumer in the presence of information related to food waste.

In summary, consumers' valuation of extended shelf-life and an eco-certified label is positive, and it increases the likelihood of buying a milk bottle. However, although shoppers value the extended shelf-life, their valuation for the smart tag is not positive. This implies that retailers should find alternative means to enhance the communication of the extended shelf-life. For instance, easing the use of the intelligent tag once it gets to the consumer (e.g., using smart shelves that show the information even when the consumer does not have a smartphone, gamify the experience through rewards, implement a loyalty program, etc.). Table 6.1 summarizes the thesis's findings.

Table 6.1: Summary of hypothesis and results.

	Hypothesis	Empirical results	Outcome
H1. Value of shelf-life	Consumers are willing to pay more for milk with longer shelf life, <i>ceteris paribus</i> .	Consumers are willing to pay \$0.0771 for an extra day of shelf-life.	Supported.
H2. Value of quality disclosure	Consumers are willing to pay more for milk with precise spoilage information, <i>ceteris paribus</i> .	Consumers are willing to pay \$0.67 less for a smart label over a static label.	Rejected.
H3. Value of ecolabels	Consumers are willing to pay more for milk with a food waste-related ecolabel, <i>ceteris paribus</i> .	Consumers are willing to pay \$0.73 for an ecolabel. Showing information increases the willingness to pay by \$0.66 (interaction effect) over the \$0.41 (main effect).	Supported.

6.1 Managerial and policy implications

A positive preference towards extended shelf-life and the eco-label implies that retailers can apply a dynamic price schedule to charge premiums for milk with a longer shelf-life. Moreover, to the extent that these retail premiums are reflected in wholesale prices, milk processors would have a profit incentive to enhance extended shelf-life. Additionally, retailers could frame discounting milk nearing the date label within the context of food waste to increase consumers' perception of value. Given that an eco-label would positively impact consumers' WTP, retailers could set lower discounts for milk nearing the date label as customers' valuations are more positive if framed around food waste. Finally, if retailers implement a dynamic pricing schedule, milk processors should accurately communicate the information; otherwise, the market will 'unravel.'

6.2 *Limitations and future work*

This study has several limitations that provide avenues for future research. First, we selected milk because of its impact on food waste and its relevance for retailers; however, choosing a higher-margin product may significantly impact the consumer. Moreover, given that shelf-life labels on milk are an indicator of food quality (i.e., spoilage) and *not* food safety, the risk of foodborne illness consuming pasteurized milk past its shelf date presents only minimal food safety risk in the U.S. Thus, choosing a product with an actual food safety risk may incentivize the use of the smart tag technology. Another limitation is that consumers may not fully understand the smart tag. To address this limitation, we could conduct another experiment in which respondents are given an information treatment consisting of a cognitive nudge regarding the intelligent tag and food waste to identify their preferences for the smart tag under complete information.

7 REFERENCES

- Amoako-Gyampah, K. (2007). Perceived usefulness, user involvement and behavioral intention: An empirical study of ERP implementation. *Computers in Human Behavior*, 3(23), 1232–1248.
- Amorim, P., Meyr, H., Almeder, C., & Almada-Lobo, B. (2013). Managing perishability in production-distribution planning: A discussion and review. *Flexible Services and Manufacturing Journal*, 25(3), 389–413. <https://doi.org/10.1007/s10696-011-9122-3>
- Aschemann-Witzel, J. (2018). Consumer perception and preference for suboptimal food under the emerging practice of expiration date based pricing in supermarkets. *Food Quality and Preference*, 63(July 2017), 119–128. <https://doi.org/10.1016/j.foodqual.2017.08.007>
- Badia-Melis, R., Mishra, P., & Ruiz-García, L. (2015). Food traceability: New trends and recent advances. A review. *Food Control*, 57, 393–401. <https://doi.org/10.1016/j.foodcont.2015.05.005>
- Bei, L.-T., & Cheng, T.-C. (2012, June 18). Brand power index - using principal component analysis. Retrieved from *Applied Economics*: <https://www.tandfonline.com/doi/full/10.1080/00036846.2012.690853>
- Bolos, L. A., Lagerkvist, C. J., & Nayga, R. M. (2019). Consumer Choice and Food Waste : Can Nudging Help ? *Choices*, 34(1), 1–7. <http://www.choicesmagazine.org/choices-magazine/theme-articles/examining-food-loss-and-food-waste-in-the-united-states/consumer-choice-and-food-waste-can-nudging-help>
- Buzby, J. C., & Hyman, J. (2012). Total and per capita value of food loss in the United States. *Food Policy*, 37(5), 561–570. <https://doi.org/10.1016/j.foodpol.2012.06.002>
- Cadario, R., & Chandon, P. (2020). Which healthy eating nudges work best? A meta-analysis of field experiments. *Marketing Science*, 39(3), 465–486. <https://doi.org/10.1287/mksc.2018.1128>
- Canali, M., Amani, P., Aramyan, L., Gheoldus, M., Moates, G., Östergren, K., Silvennoinen, K., Waldron, K., & Vittuari, M. (2017). Food waste drivers in Europe, from identification to possible interventions. *Sustainability (Switzerland)*, 9(1). <https://doi.org/10.3390/su9010037>
- Carlsson, F., Frykblom, P., & Liljenstolpe, C. (2003). Valuing wetland attributes : an application of choice experiments. 47, 95–103. <https://doi.org/10.1016/j.ecolecon.2002.09.003>
- Chapman, C., & McDonnell Feit, E. (2015). *R for marketing research and analytics*. New York: Springer.
- Chen, M. F., & Huang, C. H. (2013). The impacts of the food traceability system and consumer involvement on consumers' purchase intentions toward fast foods. *Food Control*, 33(2), 313–319. <https://doi.org/10.1016/j.foodcont.2013.03.022>

Chen, Y. Y., Wang, Y. J., & Jan, J. K. (2014). A novel deployment of smart cold chain system using 2G-RFID-Sys. *Journal of Food Engineering*, 141, 113–121. <https://doi.org/10.1016/j.jfoodeng.2014.05.014>

Ching-Hsing, C., Hooker, N., Jones, E., & Sam, A. (2010). Organic and conventional milk purchase behaviors in Central Ohio. *Agribusiness*, 311-326. doi:<https://doi.org/10.1002/agr.20269>

Cierpiszewski, R. (2015). Active And Intelligent Packaging Food – Research And Development – A Review. March 2014. <https://doi.org/10.2478/v10222>

Cornell University. (2007). Dairy Foods Science Notes Pasteurized vs Ultra-Pasteurized Milk Pasteurized. 2. <https://www.mendeley.com/catalogue/dairy-foods-science-notes-pasteurized-vs-ultrapasteurized-milk-pasteurized-vs-aseptic-uht-milk/>

Croissant, Y. (2020, October 02). The random parameteres (or mixed) logit model. Retrieved from Multinomial logit models: <https://cran.r-project.org/web/packages/mlogit/>

Daziano R, S. (2017). Multinomial Logit Models with Continuous and Discrete Individual Heterogeneity in R: The gmnL Package. *Journal of Statistical Software*, 79. doi:10.18637/jss.v079.i02

De Hooge, I. E., Oostindjer, M., Aschemann-witzel, J., Normann, A., Mueller, S., & Lengard, V. (2017). This apple is too ugly for me ! Consumer preferences for suboptimal food products in the supermarket and at home. *Food Quality and Preference*, 56, 80–92. <https://doi.org/10.1016/j.foodqual.2016.09.012>

Econometrics with R. (n.d.). Probit and logit regression. Retrieved from Econometrics with R: <https://www.econometrics-with-r.org/11-2-palr.html>

Ellison, B., & Lusk, J. L. (2018). Examining household food waste decisions: A Vignette approach. *Applied Economic Perspectives and Policy*, 40(4), 613–631. <https://doi.org/10.1093/aep/px059>

European Commission Health and Consumers. (2010). Guidance on the implementation of articles 11, 12, 14, 17, 18, 19 and 20 of regulation (EC) nb. 178/2002 on general food law. Retrieved from http://ec.europa.eu/food/food/foodlaw/guidance/index_en.htm

Food and Drug Administration - FDA. (2019, November 13). How to cut food waste and maintain food safety. Retrieved from U.S. Food and Drug Administration: <https://www.fda.gov/food/consumers/how-cut-food-waste-and-maintain-food-safety>

Gaukler, G. M., & Seifert, R. W. (2007). Applications of RFID in Supply Chains. *Trends in Supply Chain Design and Management*, 29–48. https://doi.org/10.1007/978-1-84628-607-0_2

Grebitus, C. (2006). Food quality from the consumer's perspective: an empirical analysis of perceived pork quality. Cuvillier Verlag, Göttingen.

Haller, K., Lee, J., & Cheung, J. (2020). Meet the 2020 consumers driving change. *Ibm*, 20. <https://www.ibm.com/thought-leadership/institute-business-value/report/consumer-2020#>

Hasselbach, J. L., & Roosen, J. (2015). Consumer Heterogeneity in the Willingness to Pay for Local and Organic Food. *Journal of Food Products Marketing*, 21(6), 608–625. <https://doi.org/10.1080/10454446.2014.885866>

Hole, A. R. (2007). Fitting mixed logit models by using maximum simulated likelihood. *Stata Journal*, 7(3), 388–401. <https://doi.org/10.1177/1536867x0700700306>

Hughner, R. S., McDonagh, P., Prothero, A., Schultz, C. J., & Stanton, J. (2007). Who are organic food consumers? A compilation and review of why people purchase organic food. *Journal of Consumer Behavior*, 94–100.

Jedermann, R., Nicometo, M., Uysal, I., & Lang, W. (2014). Reducing food losses by intelligent food logistics. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 372(2017). <https://doi.org/10.1098/rsta.2013.0302>

Johnson, L., Mudrak, E., & Parry, S. (2019). *Machine learning: short course*. Ithaca: CSCU.

Kalkbrenner, B. J., Yonezawa, K., & Roosen, J. (2017). Consumer preferences for electricity tariffs: Does proximity matter? *Energy Policy*, 107(April), 413–424. <https://doi.org/10.1016/j.enpol.2017.04.009>

Katajajuuri, J. M., Silvennoinen, K., Hartikainen, H., Heikkilä, L., & Reinikainen, A. (2014). Food waste in the Finnish food chain. *Journal of Cleaner Production*, 73, 322–329. <https://doi.org/10.1016/j.jclepro.2013.12.057>

Kim, Y. G., & Woo, E. (2016). Consumer acceptance of a quick response (QR) code for the food traceability system: Application of an extended technology acceptance model (TAM). *Food Research International*, 85, 266–272. <https://doi.org/10.1016/j.foodres.2016.05.002>

Kiritsis, D. (2011). Closed-loop PLM for intelligent products in the era of the Internet of things. *CAD Computer Aided Design*, 43(5), 479–501. <https://doi.org/10.1016/j.cad.2010.03.002>

Koivupuro, H. K., Hartikainen, H., Silvennoinen, K., Katajajuuri, J. M., Heikintalo, N., Reinikainen, A., & Jalkanen, L. (2012). Influence of socio-demographical, behavioural and attitudinal factors on the amount of avoidable food waste generated in Finnish households. *International Journal of Consumer Studies*, 36(2), 183–191. <https://doi.org/10.1111/j.1470-6431.2011.01080.x>

Kurajdová, K., Táborecká-Petrovičová, J., & Nedelová, G. (2019). Quality Attributes that Matters When Purchasing Milk by Slovak Consumers. *Scientia Agriculturae Bohemica*, 50(4), 244–250. <https://doi.org/10.2478/sab-2019-0034>

Lavelli, V. (2013). High-warranty traceability system in the poultry meat supply chain: A medium-sized enterprise case study. *Food Control*, 33(1), 148–156. <https://doi.org/10.1016/j.foodcont.2013.02.022>

Lee, P. Y., Lusk, K., Miroso, M., & Oey, I. (2015). Effect of information on Chinese consumers' acceptance of thermal and non-thermal treated apple juices: A study of young Chinese immigrants in New Zealand. *Food Quality and Preference*.

Li, T., Messer, K. D., & Kaiser, H. M. (2020). The impact of expiration dates labels on hedonic markets for perishable products. *Food Policy*, 93(August 2019), 101894. <https://doi.org/10.1016/j.foodpol.2020.101894>

McFaden, D. (1986). The choice theory approach to market research. *Marketing Science*, 275–297. <https://doi.org/10.1287/mksc.5.4.275>

McFarlane, D., Giannikas, V., Wong, A. C. Y., & Harrison, M. (2012). Intelligent products in the supply chain - 10 years on. In *IFAC Proceedings Volumes (IFAC-PapersOnline)* (Vol. 14, Issue PART 1). IFAC. <https://doi.org/10.3182/20120523-3-RO-2023.00237>

Minor, T., Hitaj, C., Kuchler, F., Skorbiansky, S., Roe, B., & Thornsbury, S. (2019). Are Consumers Willing to Pay to Reduce Food Waste? *Choices: The Magazine of Food, Farm, and Resource Issues*, 34(1), 1–7. <https://doi.org/10.22004/ag.econ.283544>

Müller, P., & Schmid, M. (2019). Intelligent packaging in the food sector: A brief overview. *Foods*, 8(1). <https://doi.org/10.3390/foods8010016>

Neff, R. A., Spiker, M., Rice, C., Schklair, A., Greenberg, S., & Leib, E. B. (2019). Misunderstood food date labels and reported food discards: A survey of U.S. consumer attitudes and behaviors. *Waste Management*, 86, 123–132. <https://doi.org/10.1016/j.wasman.2019.01.023>

Newsome, R., Balestrini, C. G., Baum, M. D., Corby, J., Fisher, W., Goodburn, K., Labuza, T. P., Prince, G., Thesmar, H. S., & Yiannas, F. (2014). Applications and Perceptions of Date Labeling of Food. <https://doi.org/10.1111/1541-4337.12086>

NRDC. (2017). WASTED : HOW AMERICA IS LOSING UP TO 40 PERCENT OF August.

Patra, D., Leisnham, P. T., Tanui, C. K., & Pradhan, A. K. (2020). Evaluation of global research trends in the area of food waste due to date labeling using a scientometrics approach. *Food Control*, 115(February), 107307. <https://doi.org/10.1016/j.foodcont.2020.107307>

Pizzuti, T., Mirabelli, G., Sanz-Bobi, M. A., & Gómez-González, F. (2014). Food Track & Trace ontology for helping the food traceability control. *Journal of Food Engineering*, 120(1), 17–30. <https://doi.org/10.1016/j.jfoodeng.2013.07.017>

Prolific. (2021). Prolific. Retrieved from <https://www.prolific.co/>

Public Health. Security and Bioterrorism Preparedness and Response Act of 2002. (2002). Improving State, Local, and Hospital Preparedness for and Response to Bioterrorism and Other Public Health Emergencies. Retrieved from <https://www.govinfo.gov/content/pkg/PLAW-107publ188/pdf/PLAW-107publ188.pdf>

Qi, D., & Roe, B. E. (2016). Household food waste: Multivariate regression and principal components analyses of awareness and attitudes among u.s. consumers. *PLoS ONE*, 11(7). <https://doi.org/10.1371/JOURNAL.PONE.0159250>

Qualtrics. (n.d.). Conjoint analysis white paper. Retrieved from Qualtrics: https://www.qualtrics.com/support/conjoint-project/getting-started-conjoints/getting-started-choice-based/conjoint-analysis-white-paper/?utm_lp=related+page

Quested, T. E., Marsh, E., Stunell, D., & Parry, A. D. (2013). Spaghetti soup : The complex world of food waste behaviours. “Resources, Conservation & Recycling,” 79, 43–51. <https://doi.org/10.1016/j.resconrec.2013.04.011>

ReFED. (2021). Roadmap to 2030: Reducing U.S. Food Waste by 50% and the ReFED Insights Engine. February.

Richter, B., & Bokelmann, W. (2018). The significance of avoiding household food waste – A means-end-chain approach. *Waste Management*, 74, 34–42. <https://doi.org/10.1016/j.wasman.2017.12.012>

Roe, B. E., Phinney, D. M., Simons, C. T., Badiger, A. S., Bender, K. E., & Heldman, D. R. (2018). Discard intentions are lower for milk presented in containers without date labels. *Food Quality and Preference*, 66(August 2017), 13–18. <https://doi.org/10.1016/j.foodqual.2017.12.016>

Schwendel, B. H., Wester, T. J., Morel, P. C. H., Tavendale, M. H., Deadman, C., Shadbolt, N. M., & Otter, D. E. (2015). Invited review: Organic and conventionally produced milk-An evaluation of factors influencing milk composition. *Journal of Dairy Science*, 98(2), 721–746. <https://doi.org/10.3168/jds.2014-8389>

Scozzafava, G., Gerini, F., Boncinelli, F., Contini, C., Marone, E., & Casini, L. (2020). Organic milk preference: is it a matter of information? *Appetite*, 144(September 2019). <https://doi.org/10.1016/j.appet.2019.104477>

Shepherd R., R. (2006). *The psychology of food choice*. Wallingford, UK: CAB International.

Skinner, G. A. (2015). Smart labelling of foods and beverages. In *Advances in Food and Beverage Labelling* (pp. 191–205). Elsevier. <https://doi.org/10.1533/9781782420934.3.191>

Smith, T. A., Huang, C. L., & Lin, B. H. (2009). Estimating organic premiums in the US fluid milk market. *Renewable Agriculture and Food Systems*, 24(3), 197–204. <https://doi.org/10.1017/S1742170509002579>

Statista. (2018). Organic consumers in the U.S. 1–30.

Statista. (2019, July). Supermarket sales share of perishable food in the United States in 2018, by product department. Retrieved from Statista: <https://www-statista-com.proxy.library.cornell.edu/statistics/237147/share-of-total-sales-of-supermarkets-within-the-us-by-department/>

Statista. (2019, July). U.S. consumption share of beverages 2018, by segment. Retrieved from Statista: <https://www-statista-com.proxy.library.cornell.edu/statistics/387199/us-consumption-share-of-beverages-by-segment/>

Statista. (2021, April). Retail sales of dairy department in the United States in 2021, by product category. Retrieved from Statista: <https://www-statista-com.proxy.library.cornell.edu/statistics/764884/dairy-retail-sales-us/>

Statista. (2021, May). Milk retail sales in the United States from 2005 to 2020 (in billion pounds). Retrieved from Statista: <https://www-statista-com.proxy.library.cornell.edu/statistics/251537/us-milk-sales/>

Stefan, V., van Herpen, E., Tudoran, A. A., & Lähteenmäki, L. (2013). Avoiding food waste by Romanian consumers: The importance of planning and shopping routines. *Food Quality and Preference*, 28(1), 375–381. <https://doi.org/10.1016/j.foodqual.2012.11.001>

Stolzenbach, S. W., LP Bredie, W., Bojesenristensen, R., & Byrne, D. (2013). Impact of product information and repeated exposure on consumer liking, sensory perception and concept associations of local apple juice. *Food Research International*.

Tarjan, L., Šenk, I., Tegeltija, S., Stankovski, S., & Ostojic, G. (2014). A readability analysis for QR code application in a traceability system. *Computers and Electronics in Agriculture*, 109, 1–11. <https://doi.org/10.1016/j.compag.2014.08.015>

The Food and Drug Administration. (2020, September 21). Tracking and tracing of food. Retrieved from <https://www.fda.gov/food/new-era-smarter-food-safety/tracking-and-tracing-food>

The Food and Drug Administration. (n.d.). Understanding date labels. Retrieved from The food and drug administration: <https://www.fda.gov/food/new-era-smarter-food-safety/tracking-and-tracing-food>

The U.S. EPA. (2020). 2018 Wasted Food Report. November.

Theotokis, A., Pramataris, K., & Tsiros, M. (2012). Effects of Expiration Date-Based Pricing on Brand Image Perceptions. *Journal of Retailing*, 88(1), 72–87. <https://doi.org/10.1016/j.jretai.2011.06.003>

Thompson, B., Toma, L., Barnes, A. P., & Revoredo-Giha, C. (2018). The effect of date labels on willingness to consume dairy products: Implications for food waste reduction. *Waste Management*, 78, 124–134. <https://doi.org/10.1016/j.wasman.2018.05.021>

Thompson, B., Toma, L., Barnes, A. P., & Revoredo-Giha, C. (2020). Date-label use and the waste of dairy products by consumers. *Journal of Cleaner Production*, 247, 119174. <https://doi.org/10.1016/j.jclepro.2019.119174>

Tsiros, M., & Heilman, C. M. (2005). The effect of expiration dates and perceived risk on purchasing behavior in grocery store perishable categories. *Journal of Marketing*, 69(2), 114–129. <https://doi.org/10.1509/jmkg.69.2.114.60762>

U.S. Census Bureau (2010). Age and sex composition. Retrieved from: <https://www.census.gov/prod/cen2010/briefs/c2010br-03.pdf>.

U.S. Department of Agriculture. (n.d.). Why should we care about food waste? . Retrieved from U.S. Department of Agriculture: <https://www.usda.gov/foodlossandwaste/why>

US FSMA. (2011, January 04). H.R. 2751 FDA food safety modernization act. Retrieved from <https://www.congress.gov/bill/111th-congress/house-bill/2751>

USDA. (2020). National Retail Report-Dairy. 87(37), 1–6.

Varian, H. (1992). *Microeconomic analysis*. New York: Norton.

Wilson, N. L. W., Miao, R., & Weis, C. S. (2019). When in Doubt, Throw It Out! The Complicated Decision to Consume (or Waste) Food by Date Labels. *Choices*, 34(1), 1–7. <https://doi.org/10.22004/ag.econ.283544>

Wilson, N. L. W., Rickard, B. J., Saputo, R., & Ho, S. T. (2017). Food waste: The role of date labels, package size, and product category. *Food Quality and Preference*, 55, 35–44. <https://doi.org/10.1016/j.foodqual.2016.08.004>

Wolf, C. A., Malone, T., & McFadden, B. R. (2020). Beverage milk consumption patterns in the United States: Who is substituting from dairy to plant-based beverages? *Journal of Dairy Science*, 103(12), 11209–11217. <https://doi.org/10.3168/jds.2020-18741>

Wong, C., McFarlane, D., Zaharudin, A., & Agarwal, V. (2002). The intelligent product driven supply chain. *IEEE International Conference on Systems, Man and Cybernetics*, 6.

Wu, J., Chang, C. T., Teng, J. T., & Lai, K. K. (2017). Optimal order quantity and selling price over a product life cycle with deterioration rate linked to expiration date. *International Journal of Production Economics*, 193(July), 343–351. <https://doi.org/10.1016/j.ijpe.2017.07.017>

Yin, S., Han, F., Chen, M., Li, K., & Li, Q. (2020). Chinese urban consumers' preferences for white shrimp: Interactions between organic labels and traceable information. *Aquaculture*, 521(May 2019). <https://doi.org/10.1016/j.aquaculture.2020.735047>

Yu, Y., & Jaenicke, E. C. (2021). The effect of sell-by dates on purchase volume and food waste. *Food Policy*, 98(September 2019), 101879. <https://doi.org/10.1016/j.foodpol.2020.101879>

8 APPENDIX

8.1 Appendix 1. Institutional review board for human participants: Notice of exemption.

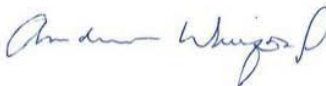


Cornell University
Office of
Research Integrity and Assurance

East Hill Office Building, Suite 320
395 Pine Tree Road
Ithaca, NY 14850
p. 607-254-5162
f. 607-255-0758
www.irb.cornell.edu

Institutional Review Board for Human Participants

Notice of Exemption

To: Aaron Adalja
From: Andrew Willford,
IRB Chairperson 
Protocol ID#: 2011009947
Protocol Title: Incentivizing consumers to help reduce retail-level fluid milk food waste
Approval Date: December 17, 2020
Expiration Date: None

Your protocol has been granted exemption from IRB review according to Cornell IRB policy and under paragraph(s) 2 of the Department of Health and Human Services Code of Federal Regulations 45CFR 46.104(d).

• Paragraph 2 allows to be exempted from IRB review research activities in which the only involvement of human subjects will be in the following category: Surveys/Interviews/Standardized Educational Tests/Observation of Public Behavior Research involving the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures or observation of public behavior if: i) information obtained is recorded in such a manner that human subjects cannot be identified, directly or through identifiers linked to the subjects; or ii) any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability or reputation.

Please note the following:

- Investigators are responsible for ensuring that the welfare of research subjects is protected and that methods used and information provided to gain participant consent are appropriate to the activity. Please familiarize yourself with and conduct the research in accordance with the ethical standards of the Belmont Report (<https://www.hhs.gov/ohrp/regulations-and-policy/belmont-report/index.html>).
- Investigators are responsible for notifying the IRB office of change or amendments to the protocol and acquiring approval or concurrence **BEFORE** their implementation.
- Progress reports, requests for personnel or other administrative changes, or requests for continuation of approval are not required for the study. However, upon conclusion of the study, please submit a Project Closure form: <http://www.irb.cornell.edu/forms>.

8.2 Appendix 2. Survey.

Q1.1 You are invited to participate in a research study about consumer milk purchasing behavior. This study is being led by Aaron A. Adalja, Assistant Professor, SC Johnson College of Business, Cornell University. **What the study is about** The purpose of this research is to improve our understanding of how consumers make decisions about purchasing dairy milk. The goal of the project is to help inform future dairy milk product offerings. **What we will ask you to do** We will ask you to complete an online survey with questions about your milk purchase behavior and economic decision-making. This will take approximately 12 minutes. **Your participation is completely voluntary**, and you may decline to answer a question or to quit the survey at any time. If you stop for any reason, your progress will be saved and you can return to complete the survey later. **Risks, benefits, and compensation for participation** We do not anticipate any risks from participating in this research. There is no direct benefit to you from taking part in this survey. You will receive compensation for your participation in this survey as specified in the terms outlined in the Prolific platform. **Privacy/Confidentiality/Data Security** Your responses to the survey will be kept confidential. All data will be stored in a password protected electronic database. Please note that the survey is being conducted with the help of Prolific, a company not affiliated with Cornell and with its own privacy and security policies that you can find at its website. We anticipate that your participation in this survey presents no greater risk than everyday use of the Internet. **Sharing De-identified Data Collected in this Research** De-identified data from this study may be shared with the research community at large to advance science. We will remove or code any personal information that could identify you before files are shared with other researchers to ensure that, by current scientific standards and known methods, no one will be able to identify you from the information we share. Despite these measures, we cannot guarantee anonymity of your personal data. **If you have questions** The main researcher conducting this study is Aaron A. Adalja, a professor at Cornell University. If you have questions, you may contact Aaron A. Adalja at aaa362@cornell.edu or at (607) 255-8971. If you have any questions or concerns regarding your rights as a subject in this study, you may contact the Institutional Review Board (IRB) for Human Participants at 607-255-5138 or access their website at <http://www.irb.comell.edu>. You may also report your concerns or complaints anonymously through Ethicspoint online at www.hotline.cornell.edu or by calling toll free at 1-866-293-3077. Ethicspoint is an independent organization that serves as a liaison between the University and the person bringing the complaint so that anonymity can be ensured. Thank you for taking the time to participate in this research!

This consent form will be kept by the researcher for five years beyond the end of the study.

Clicking the “I consent, begin the study” option indicates that you have read and understood the above information, and that you consent to take part in the study.

- I consent, begin the study. (4)
- I do not consent, finish the study. (5)

End of Block: Introduction and Consent

Start of Block: Does not consent

Q2.1 “As you do not wish to participate in this study, please return your submission on Prolific by selecting the 'Stop without completing' button.”

End of Block: Does not consent

Start of Block: Prolific ID

Q3.1 Before you proceed to the survey, please complete the captcha below.

Q3.2 Please, enter your Prolific ID here:

End of Block: Prolific ID

Start of Block: Screening Questions

Q4.1 Do you or anyone in your household consume dairy milk?

- Yes (1)
- No (2)
- Prefer not to answer (3)

Q4.2 In what country do you currently reside?

- United States (1)
- Other (2)
- Prefer not to answer (3)

Q4.3 What is your year of birth?

End of Block: Screening Questions

Start of Block: Inconsistent screening validation

Q5.1 “You are ineligible for this study, as you have provided information which is inconsistent with your Prolific prescreening responses. Please return your submission on Prolific by selecting the 'Stop without completing' button.”

End of Block: Inconsistent screening validation

Start of Block: Behaviors

Q6.1 The next few questions will ask about your household's food purchasing habits.

Q6.2 Are you the primary food shopper in your household?

- Yes (1)
- No (2)
- Prefer not to answer (3)

Q6.3 How often do you purchase dairy milk?

- Less frequently than every 14 days (1)
- Approximately every 10 - 14 days (2)
- Approximately once a week (3)
- Multiple times a week (4)
- Daily (5)
- Prefer not to answer (6)

Q6.4 How often do you consume dairy milk?

- Less than once a week (1)
- Once a week (2)
- Multiple times a week (3)
- Once a day (4)
- Multiple times a day (5)
- Prefer not to answer (6)

Q6.5 Where do you most commonly purchase dairy milk?

- Warehouse club stores (Costco, Sam's Club, BJ's, etc.) (1)

- Large/national big-box stores (Walmart, Target, K-Mart, etc.) (2)
- Large supermarkets (Harps, Tops, Sprouts, etc.) (3)
- Specialty stores (Whole Foods, Trader Joe's, ethnic grocery stores, etc.) (4)
- Small/local grocery stores (5)
- Convenience stores (6)
- Other (please specify): (7) _____
- Prefer not to answer (8)

Q6.6 Which fat content of dairy milk do you usually purchase?

- Skim (1)
- 1% Low fat milk (2)
- 2% Reduced fat milk (3)
- Whole milk (4)
- Other (please specify): (5) _____
- Prefer not to answer (6)

Q6.7 What size of dairy milk package do you usually purchase?

- Quart (1)
- Half-gallon (2)
- Gallon (3)
- More than one gallon (4)
- Other (please specify): (5) _____

Prefer not to answer (6)

Q6.8 Do you purchase lactose-free dairy milk?

Never (1)

Sometimes (2)

About half the time (3)

Most of the time (4)

Always (5)

Prefer not to answer (6)

Q6.9 Do you purchase any **non-dairy milk alternatives** (e.g., soy- or nut-based beverages)?

Never (1)

Sometimes (2)

About half the time (3)

Most of the time (4)

Always (5)

Prefer not to answer (6)

Display This Question:

If Do you purchase any non-dairy milk alternatives (e.g., soy- or nut-based beverages)? != Never

And Do you purchase any non-dairy milk alternatives (e.g., soy- or nut-based beverages)? != Prefer not to answer

Q6.10 Which types of **non-dairy milk alternatives** do you usually purchase (check all that apply)?

- Soymilk (1)
- Almond milk (2)
- Oat milk (3)
- Coconut milk (4)
- Other nut milk (5)
- Other (please specify): (6) _____
- Prefer not to answer (7)

Display This Question:

If Do you purchase lactose-free dairy milk? != Never

And Do you purchase lactose-free dairy milk? != Prefer not to answer

Q6.11 Why do you buy **non-dairy milk alternatives** (check all that apply)?

- Lactose intolerance (1)
- Milk allergy (2)
- I don't like the taste of dairy milk (3)
- Vegan / Vegetarian diet or lifestyle (4)
- Longer product shelf life (5)
- Concerns about inflammation (6)

- Concerns over antibiotics, pesticides, or hormones (7)
- Animal welfare (8)
- Other (please specify): (9) _____
- Prefer not to answer (10)

End of Block: Behaviors

Start of Block: Intro and explanations

Q7.1 In this section, we would like you to imagine that you are in your favorite grocery store and are looking to purchase **dairy milk**. Please, compare options 1, 2, and 3 on each page, and choose which one you would most prefer to purchase. Compare only the purchase options presented on each page. Do not compare these purchase options to purchase options presented on other pages of the survey.

Please assume that any **product characteristics not explicitly listed on the page are identical across all three purchase options**. For example, please **assume that the type of container, package size, and fat content are the same across all three options**.

Q7.2 **Definitions:** Please, read the following definitions before you proceed:

End of Block: Intro and explanations

Start of Block: Information treatment - Food waste messaging

Display This Question:

If Group = Treatment

Q8.1

End of Block: Information treatment - Food waste messaging

Start of Block: ConjointBlock

C1 (1/4) Assume that you are going to buy a gallon bottle of milk. If you could only choose from the following three options, which one would you choose?

Milk Option 2

- (1)
- (2)
- (3)
- (4)

C2 (2/4) Assume that you are going to buy a gallon bottle of milk. If you could only choose from the following three options, which one would you choose?

Milk Option 2

- (1)
 - (2)
 - (3)
 - (4)
-

C3 (3/4) Assume that you are going to buy a gallon bottle of milk. If you could only choose from the following three options, which one would you choose?

Milk Option 2

- (1)
- (2)
- (3)
- (4)

C4 (4/4) Assume that you are going to buy a gallon bottle of milk. If you could only choose from the following three options, which one would you choose?

Milk Option 2

- (1)
- (2)
- (3)
- (4)

End of Block: ConjointBlock

Start of Block: ConjointBlock1

Q10.1 In answering the previous four questions about hypothetical food purchase decisions, how important were each of the following attributes in your choice?
Please, drag and drop the options to place them in order of importance, with 1 being the most important and 5 being the least important.

- _____ Milk type (1)
- _____ Date label type (2)
- _____ Additional information label (3)
- _____ Date on label (4)
- _____ Price (5)

Q11.1 The next set of questions will address your household's consumption habits and perceptions.

Q11.2 On average, how often do you purchase products or services online?

- Less than once per month (1)
- About once a month (2)
- A few times a month (3)
- A few times a week (4)
- About once a day (5)
- Several times a day (6)
- Prefer not to answer (7)

Q11.3 How often have you read the information from a food label before a purchase (either online or offline) in the past month?

Definitions: A food label includes but is not limited to dates, nutritional and allergen facts, ingredients list, name of the food, amount of the product, traceability, etc.

- Never (1)
- Sometimes (2)
- About half the time (3)
- Most of the time (4)
- Always (5)
- Prefer not to answer (6)

Q11.4 Have you ever scanned a QR code within food products?

- Definitely yes (1)
- Probably yes (2)
- Might or might not (3)
- Probably not (4)
- Definitely not (5)
- Prefer not to answer (6)

End of Block: Online buying behavior and QR Code use

Start of Block: Perceptions

Q12.1 How familiar are you with food waste issues related to fluid dairy milk?

- Not familiar at all (1)
- Slightly familiar (2)
- Moderately familiar (3)
- Very familiar (4)
- Extremely familiar (5)
- Prefer not to answer (6)

Q12.2 To what extent do you agree with the following statements?

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)	Prefer not to answer (6)
I understand the difference between pasteurized and Ultra-Pasteurized (UP) milk. (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I discard milk when it passes the date printed on the container. (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I discard milk on the date printed on the container. (3)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I usually discard milk before I am able to finish the whole container. (15)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I smell milk before discarding it. (4)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

I taste milk before discarding it. (5)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I understand the printed date on milk indicates quality rather than food safety. (6)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I understand the differences between " <i>sell by</i> ," " <i>best if used by</i> ," and " <i>use by</i> " when printed on a container of milk. (7)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I understand food waste is a significant issue in the U.S. (8)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel bad when food is wasted. (9)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel it is wrong/morally reprehensible to waste food. (10)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I consider food waste when I make food choices. (11)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I like to better handle food to help reduce food waste. (12)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I like sharing my social contributions on social media. (13)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

I like being part of online/in-person networks that promote sustainability awareness (i.e., environment, social, food waste). (14)

End of Block: Perceptions

Start of Block: Demographic information

Q13.1 The next few questions will ask about your household characteristics.

3.2 What is your age?

- 25 or younger (1)
- 26-35 (2)
- 36-45 (3)
- 46-55 (4)
- 56-65 (5)
- 65 or older (6)
- Prefer not to answer (7)

Q13.3 What is your gender?

- Male (1)
- Female (2)
- Other (3)
- Prefer not to answer (4)

Q13.4 Which of the following best describes you? Multiple answers may be chosen.

- White (1)
- Middle Eastern or North African (7)
- Black or African American (2)
- American Indian or Alaska Native (3)
- Asian (including South Asian) (4)
- Native Hawaiian or Pacific Islander (5)
- Hispanic/Latino (6)
- Other (please specify): (9) _____
- Prefer not to answer (-1)

Q13.5 What is the highest level of school you have completed or the highest degree you have received?

- Less than high school degree (1)
- High school graduate (high school diploma or equivalent including GED) (2)
- Some college but no degree (3)
- Associate degree in college (2-year) (4)
- Bachelor's degree in college (4-year) (5)
- Master's degree (6)
- Doctoral degree (7)
- Professional degree (JD, MD) (8)
- Prefer not to answer (9)

Q13.6 Information about income is very important to understand. Would you please give your best guess? Please indicate the answer that includes your entire household income in (previous year) before taxes.

- Less than \$10,000 (1)
- \$10,000 to \$19,999 (2)
- \$20,000 to \$29,999 (3)
- \$30,000 to \$39,999 (4)
- \$40,000 to \$49,999 (5)
- \$50,000 to \$59,999 (6)
- \$60,000 to \$69,999 (7)
- \$70,000 to \$79,999 (8)

- \$80,000 to \$89,999 (9)
- \$90,000 to \$99,999 (10)
- \$100,000 to \$149,999 (11)
- \$150,000 or more (12)
- Prefer not to answer (13)

Q13.7 What is your marital status?

- Married (1)
- Widowed (2)
- Divorced (3)
- Separated (4)
- Never Married (5)
- Prefer not to answer (6)

Q13.8 Do you have children under 18 years old living in your household?

- Yes (1)
- No (0)
- Prefer not to answer (-1)

Q13.9 How many people are living or staying in your household?

INCLUDE everyone who is living or staying here for more than 2 months. **INCLUDE** yourself if you are living here for more than 2 months. **INCLUDE** anyone else staying here who does not have another place to stay, even if they are here for 2 months or less. **DO NOT INCLUDE** anyone who is living

somewhere else for more than 2 months, such as a college student living away or someone in the Armed Forces on deployment.

- 1 (1)
 - 2 (2)
 - 3 (3)
 - 4 (4)
 - 5 (5)
 - 6 (6)
 - More than 6 (7)
 - Prefer not to answer (8)
-

Q13.10 In which state do you currently reside?

▼ Alabama (1) ... Prefer not to answer (54)

End of Block: Demographic information
