STRATEGIES TO IMPROVE THE SHELF LIFE OF FLUID MILK FROM BUSINESS IMPACTS TO SUSTAINABILITY

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Samantha Lau

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Samantha Lau, Ph. D.

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In recent years, food waste has garnered a great deal of attention both in the U.S. and globally. This is especially important as an estimate of one third of food produced globally ends up going to waste. Food waste contributes to an unnecessary depletion of economic and environmental resources. In the United States, dairy products are among the top three largest food groups that contribute to the total volume of food wasted, with fluid milk comprising of 65% of the group.

The work here aims to improve shelf life and address food waste by: (1) providing a tool to allow for fluid milk shelf life prediction and evaluation of interventions to extend shelf life, (2) assessing the economic and environmental impact of processing plant interventions to reduce fluid milk waste, (3) exploring alternative ways to communicate and manage best-by dates in a retail setting and (4) evaluating how a poor experience with fluid milk can affect store choice and customer loyalty.

Overall, the results of these studies provide an understanding of technical tools and potential implementations that can be used to reduce fluid milk spoilage and consumer food waste behavior.

BIOGRAPHICAL SKETCH

Samantha Lau was born in Brooklyn, New York and graduated from Stuyvesant High School. She earned her B.S. in Food Science from Cornell University in 2018. While at Cornell, she conducted food safety and quality research under Dr. Carmen Moraru and Dr. Martin Wiedmann, which led her to pursue a graduate degree in the field.

Samantha began her PhD in Martin Wiedmann's Food Safety Lab at Cornell University in 2019. She has had the opportunity to work on various projects ranging from modeling to conducting a consumer survey and pilot study. She accepted a job at Kraft Heinz as an Associate Brand Manager, where uses the data analysis skillset and critical thinking she has developed during her graduate studies in her role.

To my family and friends who have supported me on this journey.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

There has been increased effort to address the food waste issue, as it has economic and environmental implications. Globally, about one third of the food produced or 1.3 billion tons is lost or wasted (Gustavsson et al., 2011). In the United States, 35% of the available food went unsold or uneaten (ReFED, 2021b). There are many definitions of food loss and food waste and here we use the Food and Agriculture Organization of the United Nations (FAO) widely accepted definition. Food loss occurs in the food production and harvest, post-harvest handling and storage, processing level while food waste occurs at the retailer and consumer level (FAO, 2019). Even though food is lost or wasted throughout the supply chain, a majority of it is from the retailer and consumer level (ReFED, 2021b, Withanage et al., 2021). In the United States, retailers and consumers are estimated to contribute to 43 billion pounds and 90 billion pounds of waste annually, respectively, representing a total value of $161.6 billion (Buzby, 2014).

Because large amounts of resources and labor has been invested in the food in its lifecycle, food waste also has environmental consequences. Uneaten food results in an unnecessary depletion of land, water, fertilizer, and energy (Mourad, 2016, Withanage et al., 2021). According to the FAO (FAO, 2019), global food waste has been estimated to generate 3.3 Giga tons of carbon dioxide equivalent (CO_2e) or 7% of total greenhouse gas emissions. Food waste also accounts for 6% of total water withdrawals and about 30% of the world’s agricultural land (FAO, 2019). Other environmental impacts include air pollution caused by farm machinery and exhaust emissions from the processing plants and the transportation of the products (Buzby and Hyman, 2012, Sun et al., 2017).

Food waste is a multi-faceted issue resulting from a combination of behaviors at the retailer and consumer level. Causes of food loss and waste at the retail level can be split into management related causes and nonmanagement related causes. Management related causes include overstocking or overpreparation of food, poor forecasting, or poor stock rotation on shelves (Mena et al., 2011, Thyberg and Tonjes, 2016). Nonmanagement related causes can include defects in food or food packaging or consumer preference for blemished or mishappened product (Thyberg and Tonjes, 2016). Factors that contribute to food waste at the consumer level occur in both the pre-consumption and consumption stage. Within the pre-consumption stage, consumers who do not plan their weekly menus or create a shopping list are most likely to buy more than needed and increased likelihood of food waste (Principato et al., 2021). The pre-consumption stage also includes impulse buying, lack of knowledge about preparation of food or appropriate portion sizes, and confusion between use-by and best-before dates (Buzby, 2014, Thyberg and Tonjes, 2016, Principato et al., 2021). In the consumption stage, food waste occurs when consumers have food scraps remaining that will not be consumed at a later point or when there are different preference and habits within families, or cooking malfunction (e.g. excessive heating of a product, spillages) (Buzby, 2014, Principato et al., 2021).

Due to the extent of food waste, there has been increased efforts and proposed policies to address the causes of food waste. These efforts include food waste tracking audits, smartphone applications that incentivize customers to buy product close to expiration dates at a discount price, and the development of intelligent refrigerators (Mourad, 2016, Qiao et al., 2017, Vo-Thanh et al., 2021). Other solutions include increasing accuracy of demand planning, increased communication between store managers and staff in stores, and improved inventory procedures (Pimentel et al., 2022). The increased awareness has led to retailers setting public zero food waste-to-landfill goal and joining food waste reduction coalitions and organizations (ReFED, 2021a). There has also been increased interest in implementing policies such as volume-based pricing waste disposal system or regulatory mandates (Thyberg and Tonjes, 2016).

A common issue in both the consumer and retailer level relates to shelf life. Product expiration is responsible for a weighted average of 17% of consumer products that are removed from the primary channel of distribution (GMA-FMI, 2008). One study showed that for a large consumer packaged goods (CPG) manufacturer, the annual cost of product waste was equivalent to 25% of annual profits, of which 65% of the volume was from product expiration (Akkaş, 2019). On the consumer end, a common issue is misinterpreting best-by dates as an indicator of food safety and prematurely throwing out products, resulting in about 20% of the consumer home waste (FDA, 2019, Kavanaugh and Quinlan, 2020). Prolonging and having a better understanding of shelf life can play a key role in reducing food waste for both consumers and retailers.

The following chapters detail studies related to methods of improving shelf life and addressing food waste using fluid milk as the model. Because dairy products are among the top three largest food groups that are wasted and fluid milk is the fifth most consumed beverage in the United States, it is an ideal candidate to model (Buzby, 2014, Statista 2019). In Chapter 2, a simulation model was developed to allow for fluid milk shelf life prediction and estimate the impact of different intervention strategies at a dairy processing plant. Chapter 3 uses the results from the model developed in Chapter 2 to determine the private and social gains to the dairy processing plant when implementing different intervention strategies to extend shelf life. Chapter 4 evaluates consumers' receptiveness to using QR code technology and explores the use of dynamic pricing strategies to reduce food waste that occurs when end of shelf-life product is either not sold or discarded by consumers. In Chapter 5, the results of a survey to assess how a poor experience with fluid milk can affect consumer grocery purchasing behavior in-store and online are described.

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CHAPTER 2

DEVELOPMENT OF A MONTE CARLO SIMULATION MODEL TO PREDICT PASTEURIZED FLUID MILK SPOILAGE DUE TO POST-PASTEURIZATION CONTAMINATION WITH GRAM-NEGATIVE BACTERIA

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ABSTRACT

Psychrotolerant gram-negative bacteria introduced as post-pasteurization contamination (PPC) are a major cause of spoilage and reduced shelf life of high-temperature, short-time pasteurized fluid milk. To provide improved tools to (1) predict pasteurized fluid milk shelf life as influenced by PPC and (2) assess the effectiveness of different potential interventions that could reduce spoilage due to PPC, we developed a Monte Carlo simulation model that predicts fluid milk spoilage due to psychrotolerant gram-negative bacteria introduced as PPC. As a first step, 17 gram-negative bacterial isolates frequently associated with fluid milk spoilage were selected and used to generate growth data in skim milk broth at 6°C. The resulting growth parameters, frequency of isolation for the 17 different isolates, and initial concentration of bacteria in milk with PPC, were used to develop a Monte Carlo model to predict bacterial number at different days of shelf life based on storage temperature of milk. This model was then validated with data from d 7 and 10 of shelf life, collected from commercial operations. The validated model predicted that the

parameters (1) maximum growth rate and (2) storage temperature had the greatest influence on the percentage of containers exceeding 20,000 cfu/mL standard plate count on d 7 and 10 (i.e., spoiling due to PPC), which indicates that accurate data on maximum growth rate and storage temperature are important for accurate predictions. In addition to allowing for prediction of fluid milk shelf life, the model allows for simulation of "what-if" scenarios, which allowed us to predict the effectiveness of different interventions to reduce overall fluid milk spoilage due to PPC through a set of proof-of-concept scenario (e.g., frequency of PPC in containers reduced from 100% to 10%; limiting distribution temperature to a maximum of 6°C). Combined with other models, such as previous models on fluid milk spoilage due to psychrotolerant spore-forming bacteria, the data and tools developed here will allow for rational, digitally enabled, fluid milk shelf life prediction and quality enhancement.

INTRODUCTION

Microbial spoilage is a contributor to food loss and waste globally and represents a challenge for maintaining the quality and expected shelf life of many foods, including fluid milk (Hoover, 2017; FAO, 2019). In the United States, dairy products are among the top 3 food groups representing the largest share of the total volume of food lost or wasted, with fluid milk responsible for approximately 65% of food wasted in volume attributed to dairy products (Buzby et al., 2014). The value of fluid milk loss in the US is estimated to be $6.4 billion per year (Buzby et al., 2014). Globally, fluid milk production, processing, and transport is estimated to be responsible for 2.4 kg of CO_2 equivalents (CO_2e) per kilogram of milk (FAO, 2010). Thus, reducing the volume of fluid milk wasted represents an opportunity with potential for economic and environmental impact.

Although the quality of fluid milk and dairy products can be degraded via different mechanisms (e.g., chemical, microbial), microbial growth is the predominant mechanism for pasteurized fluid milk spoilage (Martin et al., 2016). One of the main causes of microbial fluid milk spoilage is post-pasteurization contamination (PPC) with gram-negative bacteria during processing. Existing data show that in the United States approximately 50% of HTST-pasteurized fluid milk spoilage is due to PPC (Alles et al., 2018; Reichler et al., 2018). Although PPC can introduce a variety of different organisms, key organisms of concern for their potential to cause spoilage are those that can grow in refrigerated fluid milk (e.g., around 6°C). Most studies suggest that the majority of fluid milk spoilage is caused by psychrotolerant non-coliform gram-negative bacteria from the genus *Pseudomonas* (Ranieri and Boor, 2009; Martin et al., 2018; Reichler et al., 2018). When these organisms are introduced to fluid milk as a result of PPC, they usually grow to >20,000 cfu/mL over 10 d, resulting in shelf life that is typically at least 5 to 7 d shorter, compared with fluid milk that is only contaminated by psychrotolerant gram-positive spore-formers (Ranieri and Boor, 2009). Identification of strategies to reduce PPC has potential to reduce the overall amount of fluid milk spoilage and extend shelf life, which would hence reduce fluid milk waste.

Both identification of PPC and implementation of PPC control strategies can be challenging. Key challenges with identification of PPC include, but are not limited to the following: (1) PPC can often occur at low levels (e.g., <10 cfu per container), requiring tedious microbiological methods for identification; (2) the nature of contamination is frequently sporadic; and (3) a large number of possible root causes for PPC exist, ranging from improperly designed or implemented cleaning and sanitation approaches to procedures that facilitate cross-contamination (Sunga et al., 1970; Schröder, 1984; Gruetzmacher and Bradley, 1999; Reichler et al., 2018). Interventions to reduce PPC in a plant can include enhancing good manufacturing practices and cleaning sanitation procedures, improving preventative maintenance, as well as improving sanitary equipment and plant design (Reichler et al., 2020; Murphy et al., 2021). Another hurdle to reducing PPC is the difficulty of assessing the expected effects of interventions on fluid milk shelf life, thus hampering the ability of companies to assess the potential return on investment that could be achieved with different interventions.

One solution to support improved decision-making regarding selection and implementation of PPC interventions is to use modeling approaches. To that end, we report the development and validation of a Monte Carlo simulation model of pasteurized fluid milk spoilage due to PPC to estimate the concentration of gram-negative bacteria throughout shelf life and predict the effects of different intervention strategies.

MATERIALS AND METHODS

Identification and Selection of Bacterial Representatives of PPC

Data reported in a previous comprehensive study of pasteurized fluid milk spoilage in 10 processing plants across the northeastern United States (Reichler et al., 2018) were used to select representative bacterial genera, species, and strains that are commonly associated with fluid milk spoilage due to PPC, for determination of growth parameters needed for the development of the fluid milk model reported here. In the Reichler et al. (2018) study, a total of 459 gram-negative isolates obtained from fluid milk samples with PPC were characterized by 16S rDNA sequencing and assigned a sequence type (ST) based on an approximately 552-nucleotide region (Reichler et al., 2018). Data from 16S rDNA were also used to assign isolates to genus and species. In this study, using the Reichler et al. (2018) data set, Pseudomonas groups were then assigned to 1 of 8 phylogenomic groups based on the species (i.e., groups of related Pseudomonas species, such as the Pseudomonas fluorescens group), adapted from the group assignment method used by Garrido-Sanz et al. (2016). Specifically, isolates from the Reichler et al. (2018) data set were assigned to the previously defined groups from the Garrido-Sanz et al. (2016) study based on species; we then divided the largest group (P. fluorescens group) into clades. Data on the frequency of different ST among the characterized 459 isolates of gram-negative bacteria (Table 2.1) were used to select 17 isolates for growth experiments.

Table 2.1. Numbers and prevalence of Gram-negative 16S sequence types (ST) obtained from pasteurized milk collected from 10 processing plants over 3.5 years based on data reported by Reichler et al. (2018)

Genus	Species	ST	Total number of isolates across 459 isolates	Frequency (%)[1]	Selected for growth experiments	*Pseudomonas* group for ST isolated ≥ 5 times
Pseudomonas	*poae*	9	41	8.93	X	*P.fluorescens*
Pseudomonas	*fragi*	13	41	8.93	X	*P.fragi*
Pseudomonas	spp.	16	33	7.19		*P.fluorescens*
Pseudomonas	*tolaasii*	52	32	6.97	X	*P.fluorescens*
Pseudomonas	*lundensis*	11	23	5.01		*P.chloraphis*
Pseudomonas	*orientalis*	23	20	4.36	X	*P.fluorescens*
Pseudomonas	spp.	51	14	3.05		*P.fluorescens*
Pseudomonas	*grimontii*	100	14	3.05	X	*P.fluorescens*
Acinetobacter	*haemolyticus*	2	10	2.18	X	
Stenotrophomonas	*rhizophila*	41	10	2.18	X	
Pseudomonas	spp.	33	8	1.74		*P.fluorescens*
Acinetobacter	*guillouiae*	1	7	1.53		

Lelliottia	*amnigena*	17	7	1.53	X	
Pseudomonas	*taiwanensis_fulva_plecoglossicida_sl*[2]	6	6	1.31	X	*P.putida*
Hafnia	*paralvei*	36	6	1.31	X	
Rahnella	*aquatilis*	56	6	1.31	X	
Pseudomonas	spp.	85	6	1.31		*P.fluorescens*
Pseudomonas	*brassicacearum_migulae_sl*[2]	24	5	1.09	X	
Pseudomonas	spp.	67	5	1.09		*P.fragi*
Pseudomonas	spp.	78	5	1.09		*P.mandelii*
Pseudomonas	spp.	82	5	1.09		*P.mandelii*
Pseudomonas	spp.	10	4	0.87		
Raoultella/Kluyvera	spp.	71	4	0.87		
Pantoea	*anthophila*	75	4	0.87	X	
Pseudomonas	spp.	83	4	0.87		
Limnohabitans	*cf_planktonicus*	3	3	0.65		
Comamonas	*cf_koreensis*	4	3	0.65		
Pseudomonas	spp.	14	3	0.65		
Psychrobacter	spp.	30	3	0.65		
Comamonas	*cf_thiooxydans*	54	3	0.65		
Obesumbacterium	*proteus*	81	3	0.65	X	
Pseudomonas	spp.	128	3	0.65		
Pseudomonas	spp.	15	2	0.44		
Raoultella or Citrobacter	spp.	18	2	0.44		
Pseudomonas	spp.	20	2	0.44		
Pseudomonas	spp.	21	2	0.44		
Pseudomonas	spp.	22	2	0.44		
Citrobacter/Raoultella/Kluyvera	spp.	34	2	0.44		

Buttiauxella	spp.	49	2	0.44
Enterobacter	*ludwigii*	53	2	0.44
Pseudomonas	spp.	60	2	0.44
Serratia	*quinivorans*	61	2	0.44
Pseudomonas	spp.	62	2	0.44
Rahnella	*cf_aquatilis*	65	2	0.44
Rahnella	*aquatilis*	68	2	0.44
Pseudomonas	spp.	73	2	0.44
Yersinia	*kristensenii_bercovieri_sl*[2]	74	2	0.44
Pseudomonas	spp.	95	2	0.44
Hafnia	*paralvei*	96	2	0.44
Pseudomonas	spp.	106	2	0.44
Pseudomonas	spp.	108	2	0.44
Obesumbacterium	*proteus*	110	2	0.44
Pseudomonas	spp.	116	2	0.44
Pseudomonas	spp.	117	2	0.44
Pseudomonas	spp.	127	2	0.44
Pseudomonas	spp.	132	2	0.44
Pseudomonas	spp.	146	2	0.44
Citrobacter	*farmeri*	5	1	0.22
Aeromonas	*jandaei_media_hydrophila_sl*[2]	7	1	0.22
Pseudomonas	spp.	8	1	0.22
Pseudomonas	spp.	12	1	0.22
Janthinobacterium	*lividum*	19	1	0.22
Pseudomonas	spp.	35	1	0.22
Hafnia	*paralvei*	37	1	0.22
Hafnia	*paralvei*	38	1	0.22
Pseudomonas	spp.	39	1	0.22
Hafnia	*paralvei*	40	1	0.22

Hafnia	*paralvei*	42	1	0.22	
Janthinobacterium	*lividum*	43	1	0.22	
Citrobacter	*gillenii*	46	1	0.22	
Shewanella	*hafniensis*	47	1	0.22	
Buttiauxella	*brennerae*	48	1	0.22	X
Pseudomonas	spp.	50	1	0.22	
Pseudomonas	spp.	57	1	0.22	
Pseudomonas	spp.	59	1	0.22	
Raoultella	*ornithinolytica*	63	1	0.22	
Pseudomonas	spp.	64	1	0.22	
Cedecea	*davisae*	66	1	0.22	
Acinetobacter	*haemolyticus*	70	1	0.22	
Massilia	*aurea*	72	1	0.22	
Janthinobacterium	*lividum*	76	1	0.22	
Pseudomonas	spp.	77	1	0.22	
Hafnia	*paralvei*	79	1	0.22	
Pseudomonas	spp.	80	1	0.22	
Obesumbacterium	*proteus*	84	1	0.22	
Klebsiella	*pneumoniae*	86	1	0.22	
Pseudomonas	spp.	87	1	0.22	
Pseudomonas	spp.	88	1	0.22	
Pantoea	*anthophila*	89	1	0.22	
Pseudomonas	spp.	90	1	0.22	
Hafnia	*cf_paralvei*	91	1	0.22	
Serratia	*proteamaculans*	92	1	0.22	X
Buttiauxella	*brennerae*	93	1	0.22	
Citrobacter	*gillenii*	94	1	0.22	
Pseudomonas	spp.	97	1	0.22	
Obesumbacterium	*cf_proteus*	98	1	0.22	

Hafnia	*cf_paralvei*	99	1	0.22	
Janthinobacterium	*lividum*	101	1	0.22	
Janthinobacterium	*lividum*	102	1	0.22	X
Brevundimonas	*vesicularis_(T);_LMG_2350*	105	1	0.22	
Pseudomonas	spp.	107	1	0.22	
Chryseobacterium	*shigense_luteum_sl*[2]	109	1	0.22	
Pseudomonas	spp.	111	1	0.22	
Pseudomonas	spp.	112	1	0.22	
Citrobacter	*murliniae_braakii_sl*[2]	113	1	0.22	
Yersinia	*kristensenii*	114	1	0.22	
Pseudomonas	spp.	115	1	0.22	
Pseudomonas	spp.	119	1	0.22	
Serratia	*grimesii*	120	1	0.22	
Serratia	*sp_glossinae_marcescens*	122	1	0.22	
Sphingobacterium	*kitahiroshimense*	125	1	0.22	
Pseudomonas	spp.	129	1	0.22	
Pseudomonas	spp.	131	1	0.22	
Obesumbacterium/Hafnia	*proteus_paralvei_sl*[2]	133	1	0.22	
Obesumbacterium	*proteus*	134	1	0.22	
Obesumbacterium/Hafnia	*proteus_paralvei_sl*[2]	135	1	0.22	
Hafnia	*alvei*	141	1	0.22	
Sphingobacterium	*kitahiroshimense*	142	1	0.22	
Rahnella	*aquatilis*	143	1	0.22	
Buttiauxella	*izardii*	144	1	0.22	
Leclercia	*adecarboxylata*	145	1	0.22	
Serratia	*quinivorans*	147	1	0.22	
Pseudomonas	spp.	148	1	0.22	
Janthinobacterium	*sp_agaricidamnosum_lividum*	149	1	0.22	
Janthinobacterium	*lividum*	150	1	0.22	

[1] Due to significant digits, the total frequency adds up to above 100%.
[2]s.l.= sensu lato; in the broad sense.

Analysis of the Reichler et al. (2018) data set revealed that the majority of isolates linked to PPC were identified as *Pseudomonas* spp. (324 out of 459 isolates). Fifteen *Pseudomonas* ST were isolated ≥5 times and represented the most frequent *Pseudomonas* ST identified in this study. These 15 ST represented 5 of the 9 proposed *Pseudomonas* groups (e.g., P. fluorescens group, *Pseudomonas* fragi group), but also included 1 ST (ST 24) that could not be unambiguously classified to species and may represent 1 of 2 *Pseudomonas* groups (*Pseudomonas* mandelii or *Pseudomonas* corrugata). The ST classified into the *P. fluorescens* group represented 7/15 *Pseudomonas* ST isolated ≥5 times and 4 of the 6 major 16S clades within the P. fluorescens group. To provide representation of the *Pseudomonas* most commonly associated with PPC, we selected (1) the ST most commonly isolated in each of the 4 P. fluorescens clades (e.g., *P. fluorescens* clade 5; Table 2.1) as well as (2) the ST found most frequently among each of the 4 other *Pseudomonas* groups that were represented among this data set; the specific isolate representing each ST was randomly selected (using a random number generator) for inclusion in the growth experiments. Although this process yielded 8 different *Pseudomonas* isolates (4 from the P. fluorescens group and 4 from other *Pseudomonas* groups, including *P. fragi*, *Pseudomonas* chloraphis, *Pseudomonas* putida, and *P. mandelii*) that were used for growth curve experiments, a P. chloraphis isolate initially selected was removed from the final data set due to a contamination event.

In addition to *Pseudomonas*, the isolates reported by Reichler et al. (2018) as linked to PPC also included the genera *Buttiauxella*, *Hafnia*, *Lelliottia*, *Obesumbacterium*, *Pantoea*, *Rahnella*, *Serratia*, *Janthinobacterium*, *Acinetobacter*, *Comamonas*, and *Stenotrophomonas*. For 10 of these 11 genera of gram-negative bacteria, 1 isolate representing the most common ST was randomly selected for inclusion in the growth experiments (a *Comamonas* isolate was not included, due to a laboratory error); if multiple ST included the same number of isolates (e.g., each of the 5 *Janthinobacterium* isolates represented a different ST), 1 ST was randomly selected. *Janthinobacterium* spp. isolate FSL R10-0933 (ST 76), which was initially selected, did not grow in brain heart infusion (BHI) broth incubated at 32°C and was replaced with another *Janthinobacterium* spp. isolate, FSL R10-1587 (ST 102). Overall, this approach yielded 17 isolates (7 *Pseudomonas*, 7 *Enterobacteriaceae*, and 3 other genera of non-*Enterobacteriaceae* gram-negative bacteria) that were used for growth experiments (Table 2). The FSL numbers of strains refer to the Food Science Laboratory at Cornell University. Additional isolate information can be found via the Food Microbe Tracker Database (www.foodmicrobetracker.com; Vangay et al., 2013).

Table 2.2. Genus and species identification, 16S sequence type (ST), and growth parameters for the 17 isolates from pasteurized fluid milk[1]

Genus	Species[2]	FSL ID	ST	Lag (h)[3]	μ_{max} (ln CFU/h)	μ_{max_adj} (ln CFU/h)	N_{max} (log_{10} CFU/mL)	Best fitting growth model
Pseudomonas	*fragi*	R10-0056	13	25.2	0.100	0.069	9.07	Gompertz
	poae	R10-0084	9	<4[3]	0.107	0.073	8.39	Gompertz
	tolaasii	R10-0553	52	11.6	0.089	0.061	8.38	Gompertz
	orientalis	R10-0908	23	25.5	0.125	0.086	8.08	Gompertz
	grimontii	R10-1432	100	<4[3]	0.141	0.096	8.04	Gompertz
	taiwanensis_fulva_plecoglossicida_sl	R10-0990	6	20.9	0.098	0.067	7.81	Gompertz
	brassicacearum_migulae_sl	R10-0151	24	7.4	0.086	0.059	8.32	Gompertz
Buttiauxella	*brennerae*	R10-0531	48	34.9	0.081	0.056	8.51	Baranyi
Hafnia	*paralvei*	R10-3286	36	<4[3]	0.114	0.078	9.04	Gompertz
Lelliottia	*amnigena*	R10-1099	17	26.3	0.079	0.054	9.08	Gompertz
Obesumbacterium	*proteus*	R10-1113	81	28.4	0.078	0.053	9.20	Gompertz
Pantoea	*anthophila*	R10-0941	75	<4[3]	0.085	0.058	8.57	Gompertz
Rahnella	*aquatilis*	R10-0701	56	11.2	0.122	0.083	8.24	Baranyi
Serratia	*proteamaculans*	R10-1344	92	12.3	0.133	0.091	8.89	Gompertz
Janthinobacterium[4]	*lividum*	R10-1587[2]	102	<4[3]	0.058	0.040	7.82	Gompertz
Acinetobacter	*haemolyticus*	R10-2381	2	20.4	0.094	0.064	7.35	Gompertz
Stenotrophomonas	*rhizophila*	R10-1181	41	7.4	0.075	0.051	8.17	Baranyi

[1]FSL ID = Food Science Laboratory (Cornell University) identification; μmax = maximum growth rate by ST; μmax_adj =

adjusted maximum growth rate by ST; Nmax = maximum microbial population by ST.
[2]sl = sensu lato ("in the broad sense").
[3] <4: during first 12 h of the growth experiments, bacterial cultures were enumerated every 4 h.
[4]The initial *Janthinobacterium* isolate chosen for growth experiments was isolate FSL R10-0933; this isolate did not grow in liquid brain heart infusion medium, and *Janthinobacterium lividum* isolate FSL R10-1587 was chosen as a replacement isolate.

Determination of Cold-Growth Characteristics at 6°C

To determine cold-growth characteristics in skim milk broth (SMB; Becton, Dickinson and Co.), all selected isolates were streaked from frozen culture stocks onto BHI agar (Becton, Dickinson and Co.). Following 24-h incubation at 32°C, a single colony was selected from the BHI plate and used to inoculate 5 mL of BHI broth, which was subsequently incubated overnight (approximately 12–18 h) at 32°C. Bacterial numbers in the overnight BHI cultures were enumerated by plating appropriate dilutions on BHI plates, which were subsequently incubated at 32°C for 24 h; the undiluted overnight cultures were stored during these 24 h at 4°C before being used for inoculation of SMB. The enumeration results were used to determine the volume and dilution necessary to inoculate SMB at a starting concentration of approximately 103 cfu/mL. The inoculated SMB was incubated at 6°C, and bacterial numbers were enumerated (with 2 technical replicates) every 4 h during the first 12 h to capture the lag phase, every 12 h during the next 60 h, and every 24 h until 2 time points were taken during the stationary phase so that we could fully capture the exponential phase. The cold-growth characteristics for each isolate were determined based on at least 3 separate biological replicates of the experiment. Isolate cold-growth data were managed in Excel (version 2108, Microsoft Corp.) and were joined and cleaned in R version 3.6.2 (R Core Team, 2019).

Determining Cold-Growth Parameters

The nlsMicrobio package version 0.0-1 (Baty and Delignette-Muller, 2017) in R version 3.6.2 (R Core Team, 2019) was used to fit the data for the 3 biological replicates to the Buchanan (Buchanan et al., 1997), Baranyi (Baranyi and Roberts, 1994), and Gompertz (Zwietering et al., 1991) growth models (Table 2). The Bayesian information criterion values calculated with the AICcmodavg package version 2.3-1 (Mazerolle 2020) in R version 3.6.2 were used to select the growth model with the best fit. Initially, for each ST, the bacterial enumeration data for each time point were averaged across biological replicates. The averaged data were plotted to estimate the starting values of the growth parameters; these starting value estimates allowed for convergence to be achieved and allowed us to use the iterative estimation procedure in the nlsMicrobio package version 0.0-1 to best fit the data (Baty et al., 2015). The averaged data were then fitted with the growth models; this approach allowed us to identify a single growth model that best fit the data; the best-fit model was selected based on Bayesian information criterion values. Fitting the averaged values also allowed for identification of outliers, using all the growth data over time. To identify potential outliers of the bacterial enumeration data, residuals of individual data points with respect to the best-fit model were retrieved; data points were considered outliers if their residuals were identified as outliers among all residuals, based on the interquartile range method (Vinutha et al., 2018). After removal of the outliers, the remaining bacterial enumeration data were fitted with the best-fit growth model again, and the growth parameters were determined for the respective ST, including (1) lag phase (h), (2) maximum growth rate (μmax, ln cfu/h), and (3) maximum cell density (log10 cfu/mL; Table 2.2).

Predictive Model Development

Model Assumptions

For the model developed here, PPC organisms were assumed to be the only cause of spoilage in each simulated half-gallon of milk (1,900 mL). Furthermore, each simulated half-gallon of milk was assigned an initial concentration, storage temperature, and ST. Each half-gallon container of milk was assumed to be stored at a constant temperature during shelf life. The baseline model comprises 10,000 iterations, and each iteration is considered to represent one lot. Here, a lot is defined as 10 fluid milk containers coming from the same processing facility and the same processing day, modeled across 14 d of shelf life; as a result, a total of 100,000 containers are simulated. For the baseline model, it was assumed that the frequency of PPC for the 10 half-gallon containers in all simulated lots was 100% (i.e., all simulated containers had PPC); however, if the assigned initial concentration was less than 1 cfu per half-gallon, it was assumed that PPC did not occur in that container.

The effects of lower frequencies of PPC using this model can be assessed by assuming that the half-gallon containers modeled here represent only a certain portion of a given lot; for example, if the processing plant expects that only 50% of a lot are to be affected by PPC, then the model developed here would represent 50% of the processing plant's lot. The other 50% of the lot would be expected to spoil due to psychrotolerant spore-forming bacteria, and spoilage patterns could be assessed with a previously published “spore-former model” (Buehler et al., 2018), or, in the case of fewer than 1 psychrotolerant spore per container, not spoil during the storage period.

When conducting our analysis, we used 20,000 cfu/mL SPC as the microbial threshold for defining spoilage in this study. This value is the upper limit of the concentration a container can reach before it is deemed unacceptable from a quality standpoint, or what we refer to as spoiled fluid milk. We appreciate that this is a conservative threshold (which ensures compliance with the US Pasteurized Milk Ordinance limits for pasteurized milk; FDA, 2019); an alternative threshold can be easily used by this model if so desired.

Model Parameters

Six parameters were included in the model developed here (Table 2.3), including (1) storage temperature (T), (2) initial concentration of gram-negative bacteria in pasteurized milk (N0), (3) frequency of different 16S rDNA ST of gram-negative bacteria as PPC (FST), (4) adjusted maximum growth rate by ST (μmax_adj), (5) lag phase by ST (tlag), and (6) maximum microbial population by ST (Nmax).

Table 2.3. Parameters used in the Monte Carlo simulation of growth of cold-tolerant Gram-negative bacteria in pasteurized milk

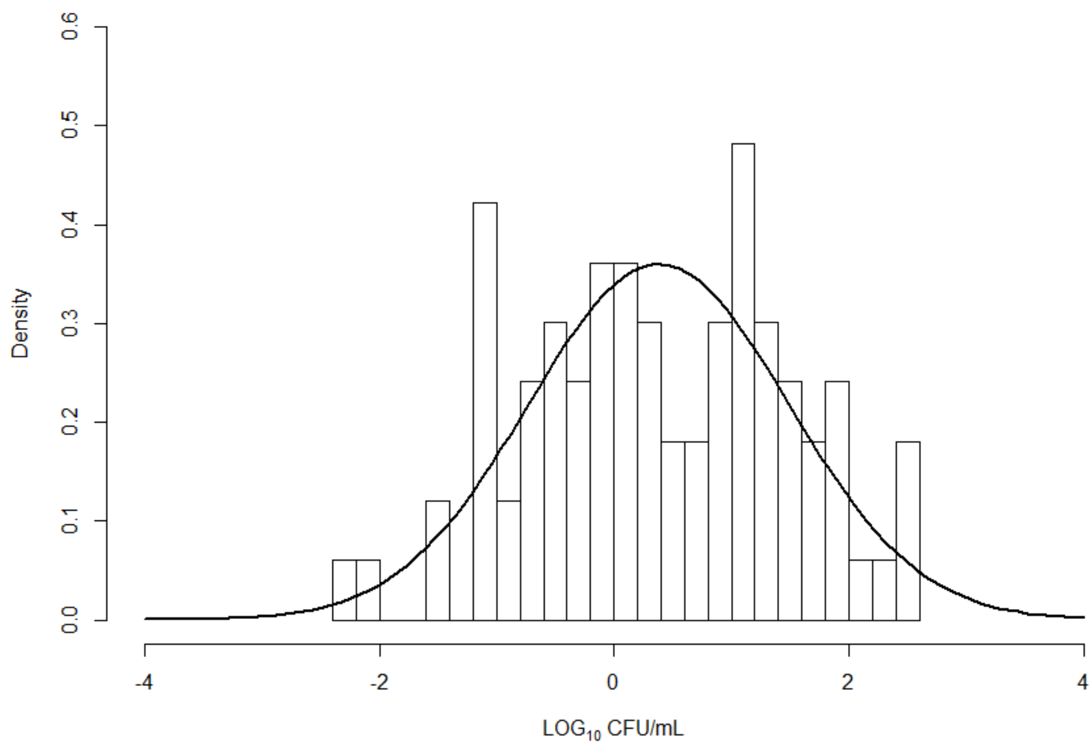
Parameter	Symbol	Variable	Unit	Distribution, value, or formula	Source
(i)	T	Storage temperature	°C	Laplace distribution (4.06°C, 2.31°C) with minimum and maximum temperature of -1°C and 15°C	Pouillot et. al, 2010
(ii)	N_0	Initial microbial population	$\log_{10}$ CFU/mL	Lognormal distribution (0.38, 1.11)	Calculated
(iii)	F_{ST}	16S sequence type frequency	%	See Table 1	Reichler et al., 2018
(iv)	μ_{max_adj}	Adjusted maximum growth rate	ln CFU per h	$\mu_{\max\ \_adj} = \mu_{\max} \times 0.684$ Buchanan: Lag phase $For\ t \leq t_{lag}$ $N_t = N_0$ Exponential growth phase $For\ t_{lag} < t < t_{max}$ $N_t = N_0 + \mu(t - t_{lag})$ Stationary phase $For\ t \geq t_{max}$ $N_t = N_{max}$ Gompertz $N_t = N_0 + (N_{max} - N_0)(e^{(-e^{(\mu e(t_{lag}-t)/(N_{max}-N_0)+1}})$ Baranyi	Based on experimental data reported here; maximum growth rate determined using the Gompertz (Zwietering et al., 1990), Baranyi (Baranyi and Roberts 1994) or Buchanan model (Buchanan et al., 1997).

				$N_t = N_0 + \mu A(t) - \ln(1 + \frac{e^{\mu A(t)} - 1}{e^{(N_{max} - N_0)}}$ $A(t) = t + \frac{1}{\mu}\ln\left(e^{-\mu t} + e^{-\mu t_{lag}} - e^{-\mu(t + t_{lag})}\right)$	
(v)	t_{lag}	Lag	h	See μ_{max_adj}	Based on experimental data reported here; lag phase determined using the Gompertz (Zwietering et al., 1990), Baranyi (Baranyi and Roberts 1994) or Buchanan model (Buchanan et al., 1997).
(vi)	N_{max}	Maximum microbial population	$\log_{10}$ CFU/mL	See μ_{max_adj}	Based on experimental data reported here; maximum microbial population determined using the Gompertz (Zwietering et al., 1990), Baranyi (Baranyi and Roberts 1994) or Buchanan model (Buchanan et al., 1997).

For parameter (1), storage temperature (T), a temperature distribution following a modified Laplace distribution was used (Table 3), based on a previous study that analyzed home refrigeration temperatures from a 2005 national survey in the US collected by Research Triangle Institute International (Pouillot et al., 2010). The minimum and maximum temperatures that could be drawn from the distribution were set at −1°C and 15°C, respectively, to prevent unrealistically low or high storage temperatures.

No primary data were available to estimate parameter (2), the initial concentration of gram-negative bacteria (N_0). Values for this parameter were thus derived from total gram-negative count data obtained during shelf life of commercially produced HTST milk collected by Cornell University's Milk Quality Improvement Program Voluntary Shelf Life (VSL) Program between January 2015 and June 2018 (N. Martin, unpublished data). Briefly, total gram-negative counts were determined by plating on crystal violet tetrazolium agar (CVTA), followed by incubation at 21°C for 48 h, and then enumeration. The VSL program has been previously described (Martin et al., 2012; Murphy et al., 2021). The criteria for microbial count data used as N0 represent only samples that were shown to spoil due to gram-negative bacteria; samples had to have enumeration of gram-negative organisms on CVTA plates. Samples that were below the detection limit, samples that had only 1 data point across shelf life, and samples that showed low levels of bacterial growth on CVTA (<1,000 cfu/mL) were not included. Of the remaining samples, we excluded those that showed low levels of bacterial growth on SPC (<20,000 cfu/mL), which would be indicative of spoilage due to spore-formers, including *Paenibacillus*, which may show growth on CVTA (N. Martin, unpublished data). Microbial count data during shelf life of the 83 samples deemed to have spoiled due to growth by gram-negative bacteria were used to estimate N_0, assuming linear growth over shelf life; a least squares regression was used to determine initial microbial concentration at d 1, which is one day after processing. With this approach, we determined a log normal distribution for this input parameter (mean = 0.38 log10 cfu/mL, SD = 1.11 $\log_{10}$ cfu/mL; Figure 2.1). The maximum initial concentration for each simulated half-gallon was set at 3 $\log_{10}$ cfu/mL to avoid simulations with unrealistically high N_0.

Figure 2.1. Initial concentrations of Gram-negative bacteria in pasteurized milk extrapolated from 83 samples collected from January 2015 to June 2018. A least squares regression equation was used to extrapolate the day 1 initial concentration. Sample data that was below the detection limit were treated as 25% of the limit value (e.g., a detection limit of 20 CFU/mL would be counted as 5 CFU/mL). A log normal distribution (black line overlay) was fitted to the extrapolated day 1 values with a mean of 0.38 $\log_{10}$ CFU/mL and a standard deviation of 1.11 $\log_{10}$ CFU/mL.



Parameter (3), the frequency of spoilage due to different ST (FST), represents the expected frequency (percentage of half-gallon containers) with which different ST occur as PPC. The frequency of an individual ST in this study was assumed to be the frequency with which that ST was isolated from fluid milk samples; for example, ST 15, which represented 0.436% of isolates characterized by Reichler et al. (2018), was assumed to be responsible for PPC of 0.436% of modeled half-gallon containers.

Growth characteristics [i.e., μ_{max_adj}, t_{lag}, and N_{max}; parameters (4), (5), and (6)] for the 17 different ST were obtained from the experimental data and subsequent growth modeling detailed earlier; values of each parameter for a given ST are shown in Table 2.2. Ratkowsky's square root model with a T_0 value of −4.15°C was used to adjust tlag and μ_{max} for different temperatures (Ratkowsky et al., 1982). This approach yielded growth parameters for 17 of 124 ST that could cause PPC in the model developed here. Growth parameters were assigned to the other 107 ST using an approach similar to that previously reported by Buehler et al. (2018). Briefly, 16S rDNA sequence data for each of the ST without experimentally obtained growth parameters ($ST_{no\ exp\ growth}$) were used to determine the most closely related ST with experimental growth data ($ST_{exp\ growth}$). For this, Basic Local Alignment Search (BLAST) was used to first determine the $ST_{exp\ growth}$ that showed the highest percentage of nucleotide similarity to each $ST_{no\ exp\ growth}$; a partial 16S rDNA maximum-likelihood phylogenetic tree of all 124 ST (Supplemental Figure S2.1, https://doi.org/10.7298/yth9-zq08; Lau et al., 2021), built based on data from Reichler et al. (2018), was used to confirm assignment of the most closely related $ST_{exp\ growth}$ in a situation where $ST_{no\ exp\ growth}$ shows equal percent similarity to 2 or 3 $ST_{exp\ growth}$. In cases where the maximum-likelihood tree would not allow for identification of the most closely related $ST_{exp\ growth}$, the growth parameters of the $ST_{exp\ growth}$ most closely related to an $ST_{no\ exp\ growth}$ were averaged, and the growth model with the lowest Bayesian information criterion value was selected as the best-fitting model.

Supplemental Figure S2.1. Maximum likelihood phylogenetic tree of representative 16S rDNA sequence types (ST) isolated from 10 HTST pasteurized fluid milk processing facilities from Reichler et al. (2018) study used to select isolates for growth. The black circle next to select ST indicates the isolates used to collect growth data in skim milk broth. The number following FSL is an isolate identification number and the data for these isolates are available in the Food Microbe Tracker database (http://www.foodmicrobetracker.com).

Model Simulations

The simulation model was programmed in R version 3.6.2 (R Core Team, 2019), predicting the concentration of PPC organisms in milk containers across 14 d of shelf life. The model was simulated for 10,000 iterations, with 10 half-gallon containers simulated per each iteration. Conceptually, this represents 10,000 unique lots and 10 half-gallon containers of milk per lot, for a total of 100,000 simulated half-gallon containers of milk. Raw data and the R code can be found on GitHub: https://github.com/FSL-MQIP/MC-2020/tree/master/Sam_FFAR_PPCmodel.

Model Validation

The model was validated with d 7 and d 10 shelf life data for milk collected by Cornell's VSL program from commercial operations between July 2018 and May 2019 (N. Martin, unpublished data); this allowed us to validate the model with data independent from those used to estimate input parameter N_0 (i.e., initial concentration of gram-negative bacteria). A total of 127 samples from this data set were used to validate the model for d 7, and a total of 145 samples from this data set were used to validate the model for d 10. These samples were identified as having spoiled due to growth by gram-negative bacteria (using the same criteria used to identify samples for estimation of N_0) and were thus deemed to represent PPC spoilage. For validation, the model was set to use a constant storage temperature of 6°C (rather than the modified Laplace distribution in Table 2.3) to reflect the storage conditions of the VSL samples used for validation. The Kolmogorov-Smirnov test, implemented using the dgof package version 1.2 (Arnold and Emerson, 2013), was used to compare the distribution of simulated counts and observed counts for 7 d and 10 d in R version 3.6.2 (R Core Team, 2019).

Sensitivity Analysis

Five model parameters, (1) storage temperature (T), (2) initial microbial concentration (N_0), (3) frequency (FST), (4) adjusted maximum growth rate (μ_{max_adj}), and (5) lag (t_{lag}), were included in the sensitivity analysis to determine the relative effects of each parameter on the percentage of containers predicted to spoil due to PPC (i.e., >20,000 cfu/mL SPC and presence of PPC) on d 7 and d 10 of shelf life; d 7 and d 10 were selected for analyses because, if there was spoilage due to PPC, this would be captured through bacterial counts on these 2 d, and data is available for d 7 and 10 with VSL samples for validation. Maximum microbial population (Nmax) was not assessed for sensitivity analysis because, under the assumption that all milk should have relatively similar concentrations of nutrients, the carrying capacity of bacteria should not change, and thus minimal change in N_{max} will occur. In one-at-a-time analyses, each respective model parameter (T, N_0, FST, μ_{max_adj}, or t_{lag}) was individually increased or decreased by 20%, 40%, and 60%, while all other model parameters were kept constant. This deterministic approach allowed us to understand the model response to extreme variations of parameter inputs and to compare different parameters with the same level of deviation. For N_0 (the initial microbial concentration) values were on a $\log_{10}$ scale, so the percent reduction was applied to the log value, not the untransformed value (e.g., a 10% reduction translates into a change from 2 $\log_{10}$ to 1.8 $\log_{10}$). For FST, sensitivity analyses were conducted by removing the ST with the fastest maximum growth rate until ST that represented 20%, 40%, and 60% of isolates were removed; for example, removal of 15 out of 125 ST that represented the fastest growth rates removed the 20% of isolates that were assigned the fastest growth rates in the original analysis. The same analyses were conducted by removing the ST with the slowest maximum growth rate until ST that represented 20%, 40%, and 60% of isolates were removed; for example, removal of the 51 ST that represented the slowest growth rates removed the 20% of isolates that were assigned the slowest growth rates in the original analysis. The effect of changes to each model parameter was assessed relative to the percentage of half-gallons of milk that were predicted by the baseline model to spoil due to PPC on d 7 and d 10.

What-If Analysis

Four what-if scenarios were used to evaluate the predicted effect of different control measures on the proportion of containers spoiled due to PPC, including (1) reducing the frequency of PPC, (2) reducing the initial concentration of organisms introduced into containers through PPC, (3) eliminating specific ST of concern, including the fastest-growing and most frequent ST, and (4) improving temperature control of fluid milk storage. For scenarios (1) through (3), different levels of change were also assessed (Table 2.4); henceforth these are referred to as "sub-scenarios." To determine how many additional days of shelf life different what-if scenarios would provide, we assessed the amount of storage time that was needed to reach a point where 34.32% of half-gallons showed bacteria numbers >20,000 cfu/mL, representing the percentage of half-gallons that reach this threshold by d 7 in the baseline model (Table 2.4). Day 7 was chosen for assessment of additional days of shelf life because it was one of the 2 d (i.e., d 7 and d 10) validated with data from commercial operations (i.e., VSL data), and validation assessing simulation data and VSL data resulted in closer alignment based on the test statistic for d 7 compared with d 10.

Table 2.4. Summary of what-if scenario evaluation

Scenarios and sub-scenarios	Implementation	Mean $\log_{10}$ CFU/mL		% of containers > 20,000 CFU/mL at		The day when > 34.32% of containers have >20,000 CFU/mL (actual % of containers with >20,000 CFU/mL) [1]
		day 7	day 10	day 7	day 10	
Baseline		3.59	4.68	34.32	56.18	7 (34.32%)
(i) Reduce frequency of PPC						
Increase periodic equipment cleaning (PEC) (taking it apart, cleaning, reassembling) of filler nozzles from once a week to twice a week.	Frequency of PPC reduced from 100% to 50%.	1.80	2.34	17.20	28.14	13 (35.59%)
Increase periodic equipment cleaning (PEC) (taking it apart, cleaning, reassembling) of filler nozzles from once a week to twice a week and replacing old filler nozzles.	Frequency of PPC reduced from 100% to 10%.	0.36	0.47	3.49	5.64	>14
(ii) Reduce initial contamination concentration						
Institute improved preventative maintenance procedures, for example SOPs and checklists to assure appropriate frequency of replacement of O-rings, gaskets, mesh screens, rubber fittings, etc., assumed to yield 1-log reduced levels of PPC organisms in different possible niches.	Starting concentration is reduced by 1 log.	2.61	3.78	21.90	42.03	9 (35.35%)

Institute improved preventative maintenance procedures, for example, SOPs and checklists to assure appropriate frequency of replacement of O-rings, gaskets, mesh screens, rubber fittings, etc., assumed to yield 3-log reduced levels of PPC organisms in different possible niches (while 3 log reduction be unrealistic under most circumstances, this provides insights into a theoretical best case scenario).	Starting concentration is reduced by 3 log.	-1.38	-0.48	7.67	17.71	>14
Use of antimicrobial coating on drains, coating is assumed to yield 2 log reduction of adherent PPC organisms.	Starting concentration is reduced by 2 log for 10% of containers.	3.35	4.45	32.22	53.41	8(39.85%)
(iii) Eliminate specific 16S rDNA sequence types of concern						
Perform "Seek and Destroy" targeting the subtype with the highest maximum growth rate (identify target 16S rDNA ST, and use environmental sampling to eliminate source). *Outcome 1:* Seek and Destroy will eliminate any PPC occurring from this source (e.g., by equipment redesign).	Set frequency of contamination with ST 100 to 0[2].	3.22	4.28	32.47	53.83	8(40.23%)
Outcome 2: Seek and Destroy will eliminate ST, but will not change overall PPC frequency (simulating a situation where frequent PPC occurs and other	Remove ST 100 from frequency table[3].	3.55	4.65	33.49	55.41	8(41.47%)

sources and ST will continue to cause PPC).						
Perform Seek and Destroy targeting the two subtypes that occur most frequently (identify these two ST and use environmental sampling to identify and eliminate source). *Outcome 1:* Seek and Destroy will eliminate any PPC occurring from the sources that harbored these two ST.	Set frequency of contamination with ST 13 and 9 to 0[4].	1.48	2.37	27.63	45.37	9(40.00%)
Outcome 2: Seek and Destroy will eliminate ST, but will not change overall PPC frequency (simulating a situation where frequent PPC occurs and other sources and ST will continue to cause PPC).	Remove ST 13 and 9 from frequency table[5].	3.56	4.64	33.74	55.56	8(41.64%)
(iv) Improved temperature control						
Having sensors that indicate when a product goes above 6°C such that the maximum temperature a product can experience is 6°C.	Temperature is truncated such that all containers cannot exceed a storage temperature of 6°C.	2.88	3.95	19.08	44.36	9(36.09%)

[1]34.32% represents the percentage of containers > 20,000 CFU/mL at day 7 for the baseline model. This is the benchmark to determine how many additional days of shelf life each intervention would provide.
[2]ST 100 has the highest adjusted maximum growth rate. Set frequency of contamination of ST 100 to 0% means elimination of ST 100 would render any container that would have been contaminated with the ST 100 as "uncontaminated." This maintains the

overall frequency of the remaining ST.
[3]Remove ST 100 from frequency table means containers that would have been contaminated with ST 100 are now contaminated with other less frequent ST.
[4]ST 13 and 9 are the most frequent ST. Set frequency of contamination of ST 13 and 9 to zero means any container that would have been contaminated with the ST 13 and 9 are rendered “uncontaminated.” This maintains the overall frequency of the remaining ST.
[5]Contamination with ST 13 and 9 are eliminated which reduces the overall frequency of contamination. Containers that would have been contaminated with ST 13 and 9 are now contaminated with other less frequent ST.

Scenario (1), which models the effects of reducing the frequency of PPC, would represent situations where a processor would implement control strategies with different levels of effectiveness in reducing the frequency with which PPC occurs. This what-if scenario included 2 sub-scenarios, one where the frequency of contaminated containers was reduced from 100% to 50%, which could represent implementation of enhanced cleaning or sanitation strategies (e.g., periodic equipment cleaning), and one where the frequency was reduced from 100% to 10%, which could represent installation of new equipment (e.g., fillers) with improved sanitary design. Scenario (2), which models the effects of reducing the initial concentration of organisms introduced into containers through PPC, would represent situations where the frequency of contamination stayed similar, but the concentration of PPC organisms introduced would be reduced; for example, through preventative maintenance, which could remove gaskets or fillers that can harbor high concentrations of PPC organisms. Scenario (2) included sub-scenarios where the initial concentration was reduced by 1 or 3 $\log_{10}$, as well as a sub-scenario that reduced initial concentration by 2 $\log_{10}$ for only 10% of containers; this sub-scenario was evaluated to determine the effect of adding an antimicrobial coating to drains. Drains were assumed to be responsible for 10% of PPC, and a previous study showed that an antimicrobial coating can reduce cell density by approximately 2 $\log_{10}$ (Werner et al., 2019). Contamination with aerosolized bacteria from drains can reach milk cartons through the use of high-pressure hoses when cleaning the floors of a processing plant (Kang and Frank, 1990).

Scenario (3), which models the effects of eliminating specific ST, would reflect situations where processors implement targeted strategies to eliminate specific subtypes of PPC organisms (e.g., through application of “Seek and Destroy,” as first described by Butts, 2003); the 2 sub-scenarios included here were (a) elimination of all contamination with ST 100, which had the highest growth rate, and (b) eliminating all contamination with the 2 most frequent ST (ST 13 and 9). For sub-scenarios (a) and (b), we also modeled 2 outcomes of the intervention, including one (“Outcome 1”) where elimination of ST would render any container that would have been contaminated with the eliminated ST or ST as “uncontaminated”; this outcome would be representative of plants with one or few well-defined niches for PPC organisms that can be eliminated through Seek and Destroy. Outcome 2, by contrast, modeled a situation where containers that were contaminated, in the baseline model, with either the ST with the highest growth rate or the 2 most frequent ST, are now contaminated with one of the remaining ST. This outcome would be typical for plants where PPC is caused by many different ST; whereas Seek and Destroy may allow for elimination of specific niches, other contamination sources will remain present and would “fill in” for the ST removed through Seek and Destroy.

Scenario (4) evaluated the effect of improved temperature control on fluid milk spoilage due to PPC; this scenario could include use of temperature sensors to verify effective implementation of this intervention. Here, we truncated the temperature to 6°C, such that the maximum temperature a product can experience is 6°C (simulating stringent temperature control during storage and distribution). Each half-gallon's assigned temperature was drawn from the previously described modified Laplace distribution; if the temperature drawn was >6°C, a new temperature would be redrawn from the distribution.

RESULTS

Gram-Negative Bacteria Representatives Commonly Associated with PPC Grow Rapidly at Low Temperatures

All 17 isolates for which cold-growth data were obtained showed >1 log10 growth in SMB incubated at 6°C. Growth modeling yielded (1) estimated lag phases ranging from <4 h to 34.9 h, (2) maximum growth rates (μ_{max}) ranging from 0.058 to

0.141 ln cfu/h, and (3) maximum cell density (N_{max}) ranging from 7.35 to 9.20 log10 cfu/mL (Table 2.2). The isolate with the highest μmax was *Pseudomonas* grimontii, isolate FSL R10-1432. The lag phase duration and μmax of 7 *Pseudomonas* spp. isolates were not significantly different ($P < 0.001$) from the 10 gram-negative bacteria that were not identified as *Pseudomonas* spp. We identified the best-fitting growth model for each of the 17 isolates using the cold-growth data; 14/17 were fitted to the Gompertz model, 3/17 were fitted to the Baranyi model, and 0/17 were fitted to the Buchanan model (Table 2.2).

Model Output and Validation

Initial validation efforts showed that our model overestimated both the frequency of spoilage due to PPC (i.e., percentage of containers with SPC >20,000 cfu/mL) and mean bacterial counts at d 7 and 10 of shelf life (Supplemental Figure S2, https://doi.org/10.7298/yth9-zq08; Lau et al., 2021). To compensate for the observed overestimation, an adjustment factor was computed based on (1) the average μmax across all 17 $ST_{exp\ growth}$ (0.098 ln cfu/h) and (2) the average μmax for the VSL samples (0.067 ln cfu/h). We used the obtained ratio of these 2 μ_{max} values (0.684) as a multiplier for each of the 17 experimentally obtained μmax values, yielding adjusted maximum growth rates (μmax_adj) for use in the model. The μmax_adj ranged from 0.040 to 0.096 ln cfu/h (Table 2.2). A Kolmogorov-Smirnov test was used to compare the distribution of simulated and observed counts (Figure 2.2). The Kolmogorov-Smirnov critical value for d 7 was 0.12, and the test statistic was 0.18 ($P < 0.001$). The Kolmogorov-Smirnov critical value for d 10 was 0.11, and the test statistic was 0.24 ($P < 0.0001$). Despite the Kolmogorov-Smirnov test showing significant differences between the model output data and the observed (validation) data, we deemed the model with the utilized input parameters to be appropriate as the baseline model that could be used for the sensitivity analyses and what-if scenario evaluation subsequently detailed. This approach is justified by the observation that differences between model predictions and observed data are minimal; for example, the mean model predicted and validation data count for d 7 were 4.8 log10 cfu/mL and 4.3 $\log_{10}$ cfu/mL, respectively, whereas the percentage of containers >20,000 cfu/mL SPC at d 7 were 66.5% and 59.1%, respectively. For d 10, the mean model predicted and validation data count were 6.3 and 6.4 log10 cfu/mL, respectively, whereas the percentage of containers >20,000 cfu/mL SPC were 95.1% and 86.9%, respectively. The validated model predicted the mean counts for d 7, 10, and 14 as 3.6 $\log_{10}$ cfu/mL, 4.7 $\log_{10}$ cfu/mL, and 5.8 $\log_{10}$ cfu/mL, respectively (Figure 2.3). The truncation on the right side of the d 10 and d 14 distributions can be explained by the ST reaching its Nmax concentration.

Figure 2.2. Density plot of the simulated concentration of PPC organisms ($\log_{10}$ cfu/mL) in fluid milk per half-gallon at (A) 7 d and (B) 10 d of storage at 6°C (solid line) and actual concentrations of PPC organisms in fluid milk per half-gallon at 7 d and 14 d of storage at 6°C, based on commercial fluid milk samples tested as part of the Voluntary Shelf life Program (VSL; dashed line). In (B) there is a peak around 8 $\log_{10}$ cfu/mL for the simulated concentration of PPC organisms which can be explained by the ST reaching its N_{max} concentration.

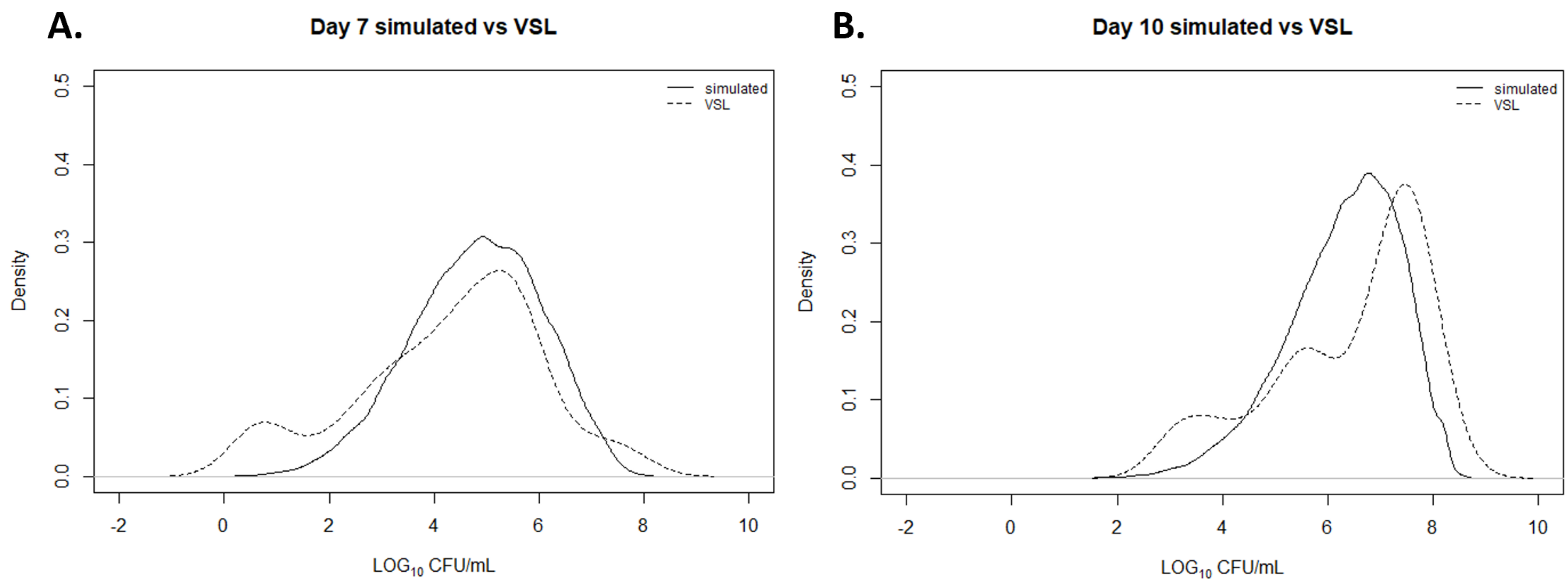
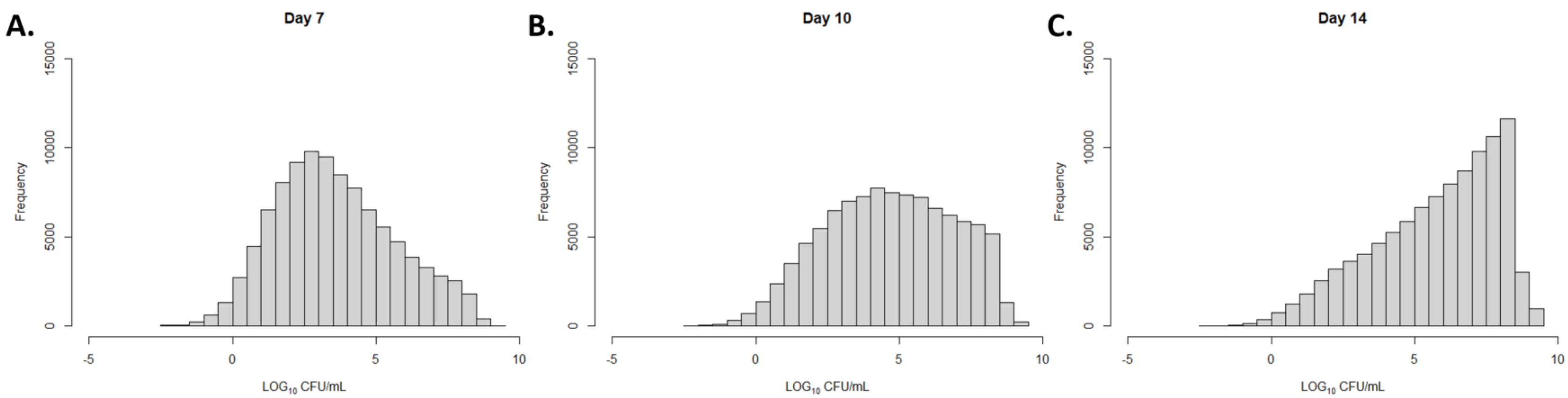


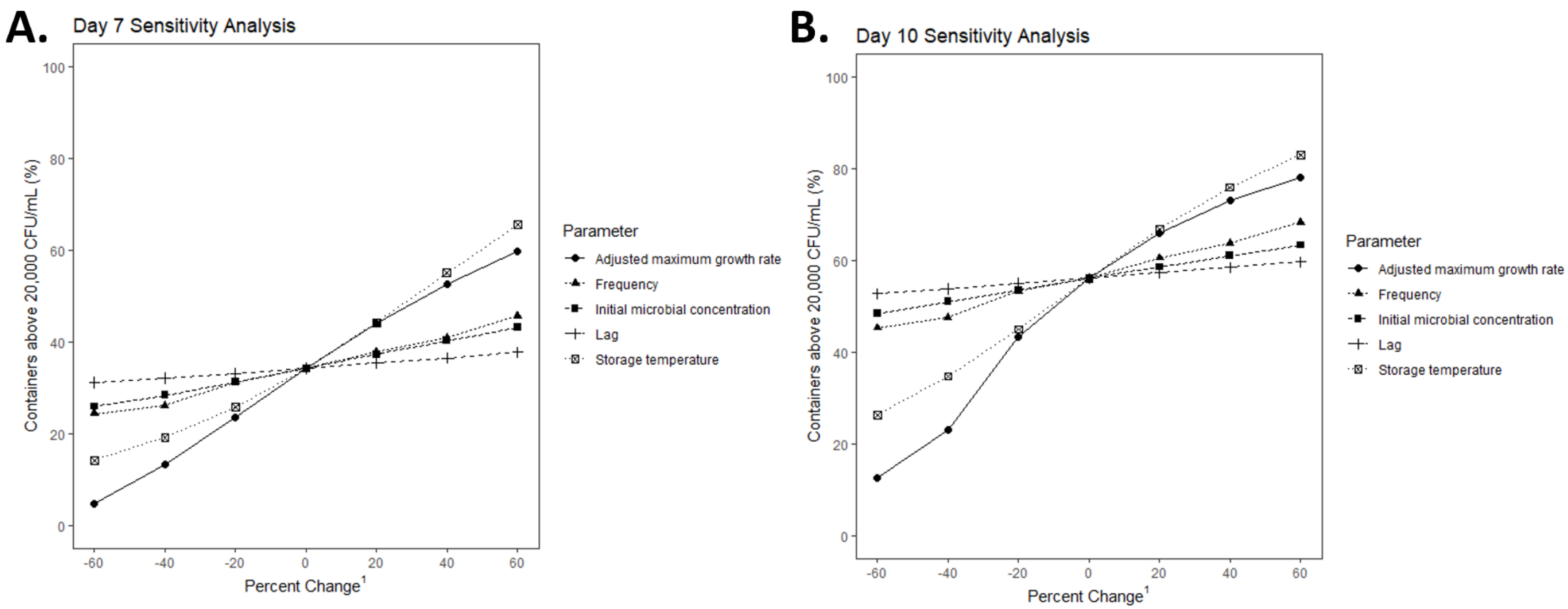
Figure 2.3. Histograms of the simulated concentration of PPC organisms in fluid milk per half-gallon over shelf life when stored at mean temperature of 4.06°C at (A) 7 d; (B) 10 d and (C) 14 d. Monte Carlo simulations comprised 10,000 iterations, and were based on six model parameters: (1) storage temperature (2) initial concentration of Gram-negative bacteria in pasteurized milk (N_0), (3) plant pasteurized milk Gram-negative bacteria ST frequency (F_{ST}), (4) maximum growth rate by sequence type (μ_{max_adj}), (5) lag phase by sequence type (tlag), and (6) maximum microbial population by sequence type (N_{max}).



Adjusted Maximum Growth Rate and Storage Temperature Have the Largest Effects on Improving the Overall Average Shelf Life of Pasteurized Fluid Milk

One-at-a-time sensitivity analyses of the 5 model input parameters (T, N0, FST, μ_{max_adj}, and t_{lag}) indicated that (1) adjusted maximum growth rate (μ_{max_adj}) and (2) storage temperature (T) had the largest effects on model outcomes, with the relative importance of these 2 parameters differing depending on whether changes were positive (i.e., an increase in temperature or an increase in adjusted maximum growth rate, both leading to increased spoilage due to PPC) or negative (i.e., a decrease in temperature or adjusted maximum growth rate). Specifically, storage temperature (T) appeared to affect outcomes more when values were increased, whereas adjusted maximum growth rate (μ_{max_adj}) appeared to be more influential when values were decreased (Figure 2.4). The parameters initial microbial concentration (N_0) and frequency (FST) showed an approximately equal influence on outcomes but were less important than adjusted maximum growth rate (μ_{max_adj}) and storage temperature (T; Figure 2.4). Finally, lag phase (t_{lag}) appeared to have the least effect on model outcomes (Figure 2.4). For example, a 60% increase of lag time (t_{lag}), which will lead to reduced spoilage due to PPC, resulted in a minimal decrease in percentage of containers with >20,000 cfu/mL at d 7 from 34.32% to 31.25% (Figure 2.4A; Supplemental Table S1, https://doi.org/10.7298/yth9-zq08; Lau et al., 2021), whereas a reduction in adjusted maximum growth rate (μ_{max_adj}) by 60% (which also reduces spoilage due to PPC), resulted in a substantial decrease in percentage of containers with >20,000 cfu/mL at d 7 from 34.32% obtained with the baseline model to 4.97% (Figure 2.4A; see Supplemental Table S1 for detailed data, Lau et al., 2021). Overall, sensitivity analysis findings were consistent regardless of whether analyses were performed using the percentage of containers with >20,000 cfu/mL on d 7 or d 10 as an outcome (Figure 2.4A and B).

Figure 2.4. Sensitivity analyses assessing the effects of varying the parameters by intervals of 20% from -60 to 60 on the percent of half-gallons of fluid milk spoiled (>20,000 CFU/mL) on (A) 7 d of refrigerated storage and (B) 10 d for different aspects of PPC growth. Percent change of 0 represents the baseline model in which the other parameters were compared to. Positive percent change represents a change to the parameter that will decrease shelf life or increase spoilage due to PPC. Negative percent change represents a change to the parameter that will increase shelf life or decrease spoilage due to PPC.



[1]The results from the lag parameter were inverted to go in the same direction as the other parameters (e.g., for Figure 2.4a., the -60 percent change should not be interpreted as a 60 percent decrease in lag. The negative percent change represents a change in the parameter that will increase shelf life and thus should be interpreted as a 60 percent increase in shelf life (i.e., 60 percent increase in lag).

Conducting What-If Scenarios Can Be Used to Evaluate the Effects of Applying Interventions

The model was used to evaluate what effects hypothetical what-if scenarios would have on predicted pasteurized fluid milk spoilage due to PPC. What-if scenarios were defined to capture possible interventions that would (1) reduce the frequency of PPC, (2) reduce the initial contamination concentration, (3) eliminate specific ST of concern, and (4) improve temperature control (Table 2.4). Metrics for effectiveness of interventions were the percentage of half-gallon containers with >20,000 cfu/mL at d 7 and 10, and the number of days of shelf life extension. These what-if analyses identified that scenario (1), reducing the frequency of PPC, had the greatest effect on increasing the shelf life of pasteurized milk, compared with the other 3 scenarios. Reducing the frequency of contamination from 100% to 50% predicted that 17.20% and 28.14% of half-gallon containers reached >20,000 cfu/mL on d 7 and 10, respectively (compared with 34.32% and 56.18% under the baseline model); reducing frequency of contamination to 10% predicted that 3.49% and 5.64% of half-gallon containers reached >20,000 cfu/mL on d 7 and 10, respectively. Using another sub-scenario, reducing the frequency of contaminated containers from 100% to 50% extended shelf life by 6 d, whereas reducing the frequency to 10% increased shelf life by >7 d (Table 2.4). By comparison, reducing the initial contamination level by 1 and 3 log10 [scenario (2); Table 2.4] reduced the percentage of containers with >20,000 cfu/mL to (1) 21.90% and 42.03% on d 7 and 10 (for 1 log10 reduction) and (2) 7.67% and 17.71% on d 7 and 10 (for 3 $\log_{10}$ reduction). Importantly, reducing initial contamination levels by 1 and 3 $\log_{10}$ yielded 0.82% and 28.80% of containers with starting inoculums of <1 cfu/container; our model was set to not allow bacterial growth in these containers, which is different from growth models that, by default, will allow for growth from levels below a single cell per container. Reducing initial contamination levels by 1 and 3 $\log_{10}$ extended shelf life by 2 and >7 d, respectively. The effect of reducing the contamination level by 2 $\log_{10}$ for 10% of containers was estimated to reduce spoilage due to PPC to 32.22% and 53.41% on d 7 and 10, respectively; this scenario simulates a "drain intervention" that reduces adhered bacteria in drains by 2 $\log_{10}$ (this includes the assumption that 10% of PPC can be traced back to drains as a source).

Another set of interventions that were evaluated with our model were hypothetical Seek and Destroy interventions, which were designed either to target the fastest growing ST or to target the 2 most frequently isolates ST. For each of these 2 sub-scenarios, the effects of 2 possible outcomes were modeled, including (1) complete elimination of the targeted ST or ST where Seek and Destroy will completely eliminate contamination originating from these sources (therefore effectively reducing the percentage of containers with PPC), and (2) elimination of the targeted ST or ST with no change in overall PPC frequency (simulating a situation where frequent PPC occurs, and other sources and ST will continue to cause PPC). Any of these sub-scenarios, regardless of which outcome was modeled, yielded increases in shelf life by only 1 to 2 d (Table 2.4). Similarly, modeling the influence of improving temperature control (in a way that would ensure that all containers would always be kept at <6°C) extended shelf life only by an estimated 2 d (Table 2.4).

DISCUSSION

Although fluid milk spoilage due to PPC is well documented as a major challenge, not many data-driven tools are available to the dairy industry to help assess and identify appropriate and effective PPC interventions. To address this gap, we collected data on the growth characteristics of gram-negative bacteria associated with PPC, which were subsequently leveraged to develop a model that simulates pasteurized fluid milk spoilage due to PPC by predicting the concentration of PPC organisms in fluid milk over shelf life. Sensitivity analysis showed that storage temperature (T) and adjusted maximum growth rate (μ_{max_adj}) had the greatest influence on the percentage of milk containers that showed bacterial counts above the threshold of 20,000 cfu/mL. Importantly, the developed model allowed for rapid simulation of what-if scenarios that can be used to evaluate the effects of different interventions on fluid milk shelf life; among the interventions modeled here, those that reduced the frequency of PPC contamination showed the greatest influence on shelf life.

A Wide Range of Gram-Negative Bacteria Can Grow in Skim Milk Broth at 6°C

The 17 isolates of gram-negative bacteria chosen to represent bacteria associated with PPC showed a wide range of lag phase duration. The selected isolates had estimated lag phase durations that ranged between less than 4 h and 34.9 h at 6°C. Among the 7 *Pseudomonas* spp. isolates characterized, estimated lag phase duration ranged from <4 to 25.5 h. This is consistent with reports from previous studies; for example, Chen et al. (2011) reported a lag phase of 9.4 h for P. fluorescens in whole UHT milk at 7°C, whereas Lin et al. (2016) reported a lag phase of 29.5 h for P. fluorescens in low-fat (1%) UHT milk at 4°C. Similarly, Stevenson et al. (2003) found that *P. fragi* in UHT skim milk at 4°C had an estimated lag phase duration of less than 24 h, whereas the lag phase duration for 4 different *P. fluorescens* ranged from 9.36 to 48.96 h. To allow us to compare our findings to those from these similar previous studies, we adjusted the previously reported lag phases for *Pseudomonas* spp. (Stevenson et al., 2003; Chen et al., 2011; Lin et al., 2016) from the original study temperature (e.g., 4°C for Stevenson et al., 2003), to 6°C (the temperature we used in our growth experiments), using Ratkowsky's square root model (Ratkowsky et al., 1982); we found that the adjusted lag phase durations ranged between 0 and 31.6 h, which is comparable to results from our study. The remaining 10 non-*Pseudomonas* isolates that were tested in our study showed lag phase durations between <4 and 34.9 h. Unlike the growth data for *Pseudomonas* spp., growth data in milk for dairy-related non-*Pseudomonas* species is lacking in the literature. Although we observed differences in the duration of lag phases for different isolates, all of these recorded lag phases are considered short in relation to the duration of a typical milk shelf life; for example, shelf life of HTST-pasteurized milk with PPC ranges from 10 to 14 d at 6°C (Reichler et al., 2018).

Overall growth rates for the 17 gram-negative bacteria most commonly associated with PPC were between 0.058 to 0.141 ln cfu/h at 6°C, which represents doubling times ranging from 4.93 to 11.8 h. Of all isolates tested, *P. grimontii* ST 100 had the highest µ*max*, at 0.141 ln cfu/h. The 2 most frequent ST in the data set, *Pseudomonas poae* and *P. fragi*, ST 9 and 13, had µmax of 0.107 and 0.100 ln cfu/h, respectively. These growth rates are lower compared with the growth rates reported by Stevenson et al. (2003), who found that in UHT skim milk at 4°C, *P. fragi* had a growth rate of approximately 0.136 ln cfu/mL, and 4 *P. fluorescens* isolates had growth rates in the range of 0.120 to 0.142 ln cfu/mL. Similarly lower growth rates were determined for all 7 *Pseudomonas* spp. (mean of 0.107 ln cfu/h, range of 0.086–0.141 ln cfu/h) and 10 non-*Pseudomonas* spp. isolates (mean of 0.092 ln cfu/h, range of 0.058–0.133 ln cfu/h) characterized during this study. More rapid growth rates of *Pseudomonas* spp. compared with non-*Pseudomonas* spp. are consistent with prior studies that found that *Pseudomonas* spp. are more frequently responsible for milk spoilage compared with other gram-negative organisms (i.e., *Enterobacteriaceae*; Ternström et al., 1993; Ranieri and Boor, 2009).

PPC Models Using Growth Parameters from Pure Culture in Skim Milk Broth Require an Adjustment Factor to Better Predict PPC

Initial validation of the PPC model developed here showed that the simulation model consistently overestimated the percentage of spoiled half-gallons on d 7 and 10 of shelf life. We reasoned that this was most likely due to the fact that growth data were collected in SMB, which may allow for more rapid growth than HTST milk. For example, presence of residual lactoperoxidase in HTST milk (which would be absent from SMB, which has undergone substantially harsher heat treatment than HTST milk) could partially inhibit growth of bacteria introduced by PPC (Reiter and Härnulv, 1984; Munsch-Alatossava et al., 2018). Lactoperoxidase plays a bactericidal role due to its ability to form oxidized compounds with antimicrobial properties (Munsch-Alatossava et al., 2018). Alternatively, or additionally, bacterial growth in actual commercial milk with PPC may also be slower compared with the growth determined in this study, since growth data in SMB were collected in pure culture, whereas commercial milk samples are likely contaminated with multiple bacterial subtypes. This is supported by Reichler et al. (2018), who found that, among 280 HTST fluid milk samples from 10 different processing plants, samples that showed SPC >20,000 cfu/mL in at least one day of shelf life had a mean of 8.5 different bacterial isolates (based on 16S sequencing). Another study that collected pasteurized milk samples from 4 processing plants also reported considerable genetic diversity of *Pseudomonas* spp. within fluid milk products, which further supports that PPC may often represent contamination with multiple strains (Dogan and Boor, 2003). Competition for limited nutrients or production of inhibitory substances by some strains (Gram et al., 2002) can explain why growth in pure cultures is faster than bacterial growth in real-life milk samples. Similarly, Xu (2021) emphasized the importance of interactions in mixed cultures, including possible coexisting interactions, where species may slow one another's growth. To address the fact that the initial model overestimated bacterial growth, we calculated an adjustment factor that adjusted the growth rates determined in SMB (0.098 ln cfu/h, which corresponds to a doubling time of 7.1 h) to the growth rates that are based on available growth data expected in pasteurized milk (0.067 ln cfu/h, which represents a doubling time of 10.3 h). Applying the adjustment factor results in a change in the test statistic of the Kolmogorov-Smirnov test from 0.65 and 0.40 for the initial model without the adjustment factor, to 0.18 and 0.24 for the model with the adjustment factor, for d 7 and 10, respectively. Once the adjustment factor was implemented in the PPC model, the model was able to more accurately predict the percentage of spoiled half-gallons for commercial milk containers.

Importantly, adjustment factors have been used in previous studies to account for certain limitations in predictive models and to tune models to predict observed real-world outcomes. For example, in a risk assessment of Listeria monocytogenes in ready-to-eat foods, researchers used an adjustment factor to account for the variability of the parameters that influence the relationship between the dose and illness severity (FDA, 2003); this adjustment factor was necessary because the lethal dose was determined using mortality data from mice studies, and adjustment was made based on Centers for Disease Control and Prevention estimates of annual death rates (FDA, 2003). Another adjustment factor was used in the risk assessment to account for overestimation of *L. monocytogenes* prevalence in ready-to-eat foods from older studies compared with recent studies that could be a result of higher actual contamination levels or nonrepresentative sampling (FDA, 2003). These adjustment factors are used to account for studies conducted with experimental animals and the limited amount of data available, respectively. Although these previous applications of adjustment factors validate our use of an adjustment factor, future experiments to identify the reason for why SMB-based growth parameters apparently overestimate fluid milk spoilage will be important, particularly as they may help identify improvements that may be needed for future models (e.g., inclusion of multiple strain interactions instead of the simplifying assumption that a given container will be contaminated with only 1 ST).

Adjusted Maximum Growth Rate and Storage Temperature Have the Greatest Influence on Predicted Concentrations of Bacteria Associated with PPC in Fluid Milk Over Shelf Life

Sensitivity analysis indicated that adjusted maximum growth rate (μ_{max_adj}) and storage temperature (T) have the strongest effects on predicted percentage of containers spoiled due to PPC on d 7 and 10 of shelf life, suggesting that accurate and sufficient data for these 2 parameters are important for the type of spoilage models developed here. The importance of maximum growth rate for estimating microbial spoilage and bacterial growth was also demonstrated by Buehler et al. (2018) using the Monte Carlo simulation model they developed to predict pasteurized fluid milk spoilage due to psychrotolerant spore-forming bacteria. Sensitivity analysis of a model that was developed to predict growth of L. monocytogenes on cheese curds also found that maximum growth rate was among the most influential parameters (Couvert et al., 2010). Similarly, in a publication that reported a general framework for quantitative microbial food safety risk assessment (McNab, 1998), maximum growth rate (designated as “growth rate after treatment”) was consistently found to be one of the top 3 ranked parameters across sensitivity analyses conducted for different specific scenarios. Likewise, previous studies have also found storage temperature to have a considerable effect on the output of different microbial risk assessment models. For example, a Monte Carlo simulation model for bacterial spoilage of fluid milk developed by Schaffner et al. (2003) predicted that decreasing storage temperature from 6.5°C to 4.4°C resulted in a reduction of spoilage (defined as samples exceeding 107 cfu/mL) due to growth of psychrotolerant organisms from 67% to 28% by d 14. Similarly, the Monte Carlo simulation model for fluid milk spoilage due to psychrotolerant spore-formers, developed by Buehler et al. (2018), predicted that reducing refrigeration temperature from 6°C to 4°C would result in a reduction of spoilage at d 21 (defined as samples exceeding 20,000 cfu/mL) from 66% to 9%. The sensitivity analysis and previous studies suggest a need to place more emphasis on gathering more accurate data on maximum growth rate and storage temperature when using models to predict microbial growth.

What-If Scenarios Can Be Used to Assess the Effects of Different Interventions on Shelf Life

The model developed here provided an opportunity to run different "what-if" (or scenario) analyses; these analyses provide an opportunity to assess the influence different intervention strategies may have on product shelf life, potentially helping industry with decision-making. The what-if analyses we conducted indicated that reducing the frequency of PPC contamination could substantially extend the shelf life of pasteurized fluid milk (e.g., increase in shelf life by 6 d if PPC frequency is reduced from 100% to 50%). Possible interventions that would be expected to reduce the frequency of contamination would be implementation of enhanced periodic equipment cleaning procedures on key equipment responsible for PPC, such as filler nozzles, or replacement of equipment or equipment components with more hygienic and easer-to-clean counterparts (e.g., replacement of poorly designed fillers, replacement of difficult-to-clean filler nozzles). The potential positive effects of these types of interventions are supported by Reichler et al. (2020) and Ralyea et al. (1998), who showed that an improved preventative maintenance program targeting rubber parts of a specific filler decreased the frequency of PPC in fluid milk containers. Additionally, Murphy et al. (2021) found that having well-designed cleaning and sanitation programs, along with appropriate training, are among the top factors necessary to reduce PPC.

Reducing the initial concentration of PPC organisms was also predicted to substantially extend the shelf life of fluid milk if reductions in initial PPC contamination levels were large (e.g., a 3 $\log_{10}$ reduction increased shelf life by >7 d, whereas a 1 log10 reduction increased shelf life by only 2 d). Although a 3 log10 reduction in initial concentration may be unrealistic under most circumstances, this analysis provides a best-case scenario for the effects of interventions that reduce initial PPC contamination levels. Interventions that decrease initial contamination levels may include instituting improved preventative maintenance procedures such as using standard operating procedures and checklists to ensure appropriate frequency of replacement of equipment parts such as O-rings, gaskets, mesh screens, and rubber fittings. Although very limited data on actual effects of specific interventions on initial PPC levels are available, one previous study did indicate that improved inspection and cleaning, as well as preventative maintenance programs, can increase the reliability of a pizza processing line and thus reduce the frequency of failures due to equipment and lead to improvement in product quality (Tsarouhas, 2007). Importantly, a quality cost model for processing plants developed by Zugarramurdi et al. (2007) also indicated that implementation of a quality assurance plan and preventative maintenance, including replacement and maintenance of equipment parts, are appropriate and economically viable strategies to improve product quality.

Although interventions that reduce frequency and levels of PPC contamination were shown to have substantial effects on enhancing average fluid milk shelf life, other strategies tested in what-if scenarios were less effective at extending shelf life. For example, eliminating specific spoilage organisms or organism sources was predicted to extend shelf life by only 1 or 2 d (assuming that these interventions would not decrease PPC levels or frequency). Even with the limited effects identified by our model, Seek and Destroy-type strategies to eliminate sources of PPC could still be valuable, if these efforts are able to decrease PPC levels or frequency. For example, previous studies have shown that Seek and Destroy interventions can successfully reduce L. monocytogenes contamination of food products from environmental sources (Malley et al., 2015). A what-if scenario also suggested that ensuring improved temperature controls (defined here as ensuring that no fluid milk containers would be exposed to >6°C) extended shelf life by only 2 d. This represents a potentially important finding, in part because temperature is one of the many food quality indicators (e.g., gas production, pH change, humidity) that can be targeted using intelligent packaging (Fuertes et al., 2016; Yousefi et al., 2019). For example, Ellouze and Augustin (2010) evaluated a biological time-temperature indicator that could successfully be used as a quality and safety indicator for ground beef and spiced cooked chicken slices under modified atmosphere across shelf life. Importantly, although our data suggested that limited average shelf life enhancement could be achieved by assuring product distribution at <6°C, future work could use our model to evaluate different temperature control strategies and their effects on shelf life. Influence of time-temperature indicators could also be more pronounced if the baseline temperature distribution included more abusive temperatures than the baseline used in our model. Importantly, our analysis only assessed spoilage due to PPC and did not assess other potential benefits of this type of indicators, such as reduced growth of L. monocytogenes, which represents a food safety hazard for which improved temperature control has been well established to reduce food safety risks (Walker et al., 1990; Chan and Wiedmann, 2008).

Although the what-if analyses conducted here provide initial insights on the effects of various intervention strategies on fluid milk shelf life, the model developed here has some limitations that will need to be addressed to enhance its value, particularly as a decision-support tool for industry. Namely, although the model developed here provides the ability to assess the potential effects of different interventions on fluid milk shelf life, additional features to facilitate decision-making should be incorporated; for example, incorporation of a cost-benefit analysis module would help industry assess the economic feasibility and return on investment for different interventions. Additionally, an alternative approach can be used for the interpretation of containers assigned an initial concentration less than 1 cfu per half-gallon. Concentrations below 1 cfu per half-gallon can be interpreted as probabilities; for example, if the assigned concentration was 0.1 cfu per half-gallon, that container would have a 10% probability of containing 1 cfu. However, this interpretation would require a change to the model structure, a process of reassigning the initial concentration with at least 1 cfu per half-gallon, and would increase the complexity of the model. Importantly, the model developed here only considers fluid milk spoilage due to PPC, yet contamination with gram-positive spore-forming bacteria can also lead to spoilage later in shelf life, which should be considered when assessing potential intervention strategies for potential influence on shelf life. For example, 2 intervention strategies evaluated here, reducing frequency of PPC from 100% to 10% and reducing the initial contamination by 3 log10, predicted that shelf life would be extended by greater than 7 d. When evaluating the what-if scenarios that extend shelf life by greater than 7 d, it would be advisable to evaluate the effects using both the current model that predicts spoilage by PPC and the previously developed spoilage model (Buehler et al., 2018) that predicts spoilage by aerobic psychrotolerant spore-formers. A future combined model would be valuable to evaluate the effects of both gram-positive spore-forming bacteria and PPC organisms.

CONCLUSIONS

Overall, the model developed here, along with other models discussed, not only represents a starting point for digital tools to help industry identify appropriate approaches for enhancing fluid milk quality, but also represents a blueprint for the type of decision-support tools that can be developed and applied to other dairy products. Importantly, these types of tools will allow for more cost-effective approaches to identify appropriate shelf life extension strategies and will reduce the need for expensive field trials. Finally, the tools developed here can also be used to estimate shelf life of fluid milk and ultimately other dairy products, which provide opportunities for improved shelf life labeling, including dynamic shelf life labeling.

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CHAPTER 3

ECONOMIC AND ENVIRONMENTAL IMPACT ANALYSIS OF PROCESSING PLANT INTERVENTIONS TO REDUCE FLUID MILK WASTE

ABSTRACT

With the increased awareness about the economic and environmental impact of food waste, many interventions along food supply chains have been proposed to address the issue. While interventions used to target this issue usually revolve around logistics and operations management, we highlight a unique solution to address this issue, specifically for fluid milk. We target the intrinsic quality of fluid milk by evaluating interventions that will extend the product shelf-life. We used data from a previous fluid milk spoilage simulation model, collected price and product information from retail stores, conducted an expert elicitation, and used hedonic price regressions to determine the private and social gains to the dairy processing plant when implementing five different interventions to extend shelf-life. Out data suggest that the value of each additional day of shelf-life is approximately $0.03 and indicate that increasing periodic equipment cleaning is the most cost-effective strategy for processing plants to achieve fluid milk shelf-life improvements, both from a firm's economic standpoint and from an environmental standpoint. Importantly, the approaches reported here will be valuable to help individual firms to generate customized facility and firm specific assessments that identify the most appropriate strategies for extending the shelf-life of different dairy products.

INTRODUCTION

Globally and nationally, food waste is increasingly being recognized as an issue. Even though the terms food loss and food waste are used interchangeably, food loss refers to the decrease in the quantity or quality of food resulting from decisions and actions by food suppliers in the chain, excluding retailers, food service providers and consumers while food waste is a result of decisions and actions by retailers, food service providers and consumers (FAO, 2019). According to the Food and Agriculture Organization of the United Nations (FAO), one third of the food produced is wasted globally (Gustavsson et al., 2011) (Gustavsson et al., 2011, FAO, 2019). Food waste has also been estimated to generate 4.4 $GtCO_2$ eq or 8% of greenhouse gases globally (Food wastage footprint & Climate Change, 2011). Specifically, in the US, dairy products are among the top three food groups representing the largest share of the total volume of food wasted, with fluid milk responsible for approximately 65% of food waste, by volume, attributed to dairy products (Buzby, 2014). The value of fluid milk waste in the US is estimated to be $6.4 billion per year (Buzby, 2014). Alongside the financial concerns associated with fluid milk waste, there are environmental implications associated with fluid milk waste. These environmental implications can be determined using carbon dioxide equivalent (CO_2e), which measures how much a greenhouse gas contributes to global warming, relative to carbon dioxide (Brander, 2012). Globally, fluid milk production, processing, and transport has been estimated to be responsible for 2.4 kg CO_2e per kg of milk and to represent 2.7% of global anthropogenic greenhouse gas emissions (FAO, 2010, Gerber, 2013). The economic and environmental consequences of fluid milk waste underline the need for targeted initiatives that can address this issue.

Many possible approaches to help tackle the food waste challenge have been reported in both the operations and retail management literature. In the operations management literature, interventions typically focus on case size, supply chain aging, manufacturer's sales incentives, replenishment workload, and minimum order rule in order to reduce product expiration (Akkas et al., 2019). In retail management, interventions typically focus on markdown management and shelf availability and allocation (Hu et al., 2016, Teller et al., 2018). Research has largely addressed food waste as a logistical problem and suggested solutions target operations and retail management. This literature, however, inadequately evaluates solutions for food waste that can improve the products intrinsically (e.g., by extending shelf-life).

There are many technologies and solutions that can be used to improve the intrinsic quality and extend the shelf-life of fluid milk, thereby also serving to mitigate food waste (e.g., by reducing the amount of product that is discarded as it exceeded the best-by date). On-farm intervention strategies can be implemented to reduce transmission of bacterial spores in raw milk that can ultimately improve the quality of the milk and reduce fluid milk waste due to microbial spoilage (Murphy et al., 2016, Martin et al., 2021). Another solution to improving the intrinsic quality of the food is through applying interventions at the processing plant. To address this, Buehler et al. (2018) and Lau et al. (2022) developed Monte Carlo models that assessed interventions processors can apply at the dairy plant to reduce fluid milk spoilage. Fluid milk is an example of a perishable good that is in a unique position whereby improvements can be made intrinsically, without the use of technologies that may have reduced consumer acceptability (e.g., use of “non clean label” additives that reduce microbial or chemical spoilage) and where shelf-life date can be extended by applying interventions at the processing plant.

In this paper, we evaluate the potential economic and environmental implications of several possible interventions that can be conducted at a dairy processing plant to reduce fluid milk waste. We leverage a previously published Monte Carlo simulation model that predicts spoilage of pasteurized fluid milk due to post-pasteurization contamination (Lau et al., 2022) to estimate the effect of different intervention strategies. We collect price and product attribute data on half-gallon milk products to then use a hedonic pricing model to estimate the value of different attributes (e.g., shelf-life). We find that the value of each additional day of shelf-life is approximately $0.03 and present data that suggest that increasing periodic equipment cleaning is the most cost-effective strategy for processing plants to achieve fluid milk shelf-life improvements.

MATERIALS AND METHODS

We compiled data from multiple sources to conduct our economic and environmental analysis. First, we used a previously developed post-pasteurization contamination model (Lau et al., 2022) to generate a dataset of the additional days of fluid milk shelf-life associated with different intervention strategies. Then, we conducted an expert elicitation to estimate the cost of implementing each intervention strategy. We also collected price and product data of half-gallons of fluid milk both in store and online. Lastly, we collected data on the environmental impact of fluid milk and parametrized it to estimate the amount of CO_2e associated with fluid milk consumption and to determine the social cost of CO_2 emissions associated with fluid milk spoilage. In the following sections, we describe in detail each of these sources of data.

Shelf-life estimation using a post-pasteurization contamination (PPC) Monte Carlo Simulation

A previously described Monte Carlo simulation model was used to predict the shelf-life of half gallon fluid milk containers when implementing five different interventions at dairy processing plants to address post-pasteurization contamination: (i) seek and destroy, (ii) improved preventative maintenance (PM) procedures, (iii) increased periodic equipment cleaning (PEC), (iv) addition of temperature sensor to half gallon packaging, and (v) application of antimicrobial coating to floor drains (Lau et al. (2022).

The first intervention, (i) seek and destroy, represents a strategy where one specific strain of spoilage bacteria that is habitually found in a specific place or niche in a facility is responsible for a substantial proportion of fluid milk spoilage issues. Addressing this issue involves finding and removing the niche and would not be an ongoing intervention; we assume that once this niche has been removed, the facility will no longer have a problem with fluid milk spoilage due to this bacterial strain.

Implementing the second intervention, (ii) improved PM procedures, can include improved standard operating procedures (SOPs) to replace equipment parts before they wear out and contribute to bacterial contamination of finished products; this is an on-going intervention that reduces overall occurrence of finished product contamination with spoilage organisms.

In addition to Clean-In-Place (CIP) sanitation regimes, periodic equipment cleaning (PEC), which is labor intensive and involves equipment disassembly, is essential to control post pasteurization contamination. Due to the manual, labor intensive nature of PEC, plants will use different PEC frequencies. As increased PEC frequency is predicted to reduce post-pasteurization contamination with spoilage organisms, we evaluated (iii) increasing PEC frequency as the third intervention.

The fourth intervention we evaluated, (iv) the addition of temperature sensors to half gallon packaging, can also be an effective way to extend the actual shelf-life of fluid milk. This intervention would be implemented by placing a temperature sensor on each milk carton. This sensor would indicate when fluid milk exceeds a target temperature range (or a given time-temperature combination threshold) and could also be used with predictive models to allow for package specific shelf-life information ("smart label") (Lau et al., 2022). These approaches can reduce unnecessary discarding of product that is not spoiled.

Because contamination can occur through aerosolized bacteria, the fifth intervention, (v) evaluated use of antimicrobial coating on floor drains, which is expected to reduce fluid milk contamination (e.g., at the packaging stage). This contamination is a result of aerosolization of bacteria found in processing plant environments (e.g., due to cleaning with high-pressure hoses) and an antimicrobial coating on the floor drains is expected to reduce bacterial numbers on floors and hence reduce the number of aerosolized bacteria. This intervention was included as an example of interventions that use infrastructure and facility improvements to extend fluid milk shelf-life.

To simulate implementation of each of the five interventions in the model, the model parameters for post-pasteurization contamination frequency as well as the inputs for initial spoilage organism concentration in fluid milk and the storage temperature were changed to reflect the expected impact of different interventions (see Table 1 for details). For example, the temperature distribution was truncated at 6°C to represent the use of a temperature sensor to remove fluid milk containers that exceed 6°C (Table 3.1).

Table 3.1. Previously developed post-pasteurization contamination (PPC) model summary

Intervention	Implementation in a processing plant	Inputs changed in the base PPC model used to evaluate the intervention effects	Implementation in the PPC model
(i) Seek and destroy	The processing plant has one main bacterial strain that causes PPC. This strain has a specific niche. This intervention involves finding and removing/remediating this niche. Assumes that this is a facility by and large has microbial contamination under control; this is an annual intervention.	Frequency	(i) Set frequency of contamination for specific strain (“ST”) to 0 (ii) Remove specific ST from frequency table
(ii) Improved preventative maintenance (PM) procedures (e.g. improving standard operating procedures (SOPs) and checklists to assure appropriate PM scope and frequency)	This processing plant only replaces equipment parts when they see obvious wear and tear or when equipment fails; they will change from this to a standard, industry best practices PM program. However, this is only one source of PPC. There are still other sources of contamination that are not addressed with this intervention.	Initial concentration	(i) Reduced by 1 $\log_{10}$ (ii) Reduced by 3 $\log_{10}$
(iii) Increase periodic equipment cleaning (PEC) (i.e. taking it apart, cleaning, reassembling) on filler nozzles from once a week to twice a week;	A processing plant only takes apart equipment once a week and will increase it to twice a week to clean and then reassemble. The plant will also replace old filler nozzles that carry an increased risk of microbial contamination, e.g., through	Frequency	(i) Reduced from 100% to 50% (ii) Reduced from 100% to 10%

includes replacement of old filler nozzles.	biofilm formation.		
(iv) Addition of temperature sensor to half gallon packaging	A temperature sensor will be placed on each milk carton. This will indicate if the product ever goes beyond 6°C. If it exceeds the temperature range, that product will be disposed of.	Temperature	Truncate temperature distribution at 6°C
(v) Application of antimicrobial coating to floor drains	An antimicrobial coating will be used on the floor drains of the processing plant to reduce the cell density of aerosolized bacteria.	Initial concentration	Initial concentration reduced by 2 $\log_{10}$ for 10% of samples

The MC model used predicts the concentration of psychrotolerant Gram-negative bacteria introduced as post-pasteurization contamination in half-gallon fluid milk containers across 14 days of shelf-life. We used this model to generate 100,000 observations for each specific implementation of a given intervention; for some interventions two different levels of implementing were modelled with 100,000 observations per level of implementation (Table 3.1). For example, for intervention (ii), improved preventative maintenance procedure, the two levels of implementation were assumed to reduce initial concentration of psychrotolerant Gram-negative bacteria by either 1 $\log_{10}$ or 3 $\log_{10}$. On the other hand, for intervention (iv), addition of temperature sensor, there only was one level of implementation (i.e. truncate temperature distribution at 6°C).

Intervention cost data

The costs associated with each intervention are based on a hypothetical 6,000 square feet fluid milk processing plant with 6 to 7 production lines and 25 drains in total. This hypothetical processing plant produces 300,000 pounds of milk per day, which is approximately 68,900 half-gallons per day. Expert elicitation (Rowe and Wright, 1999, Colson and Cooke, 2018) was conducted to approximate the costs for interventions (i)-(iii). The participants of the expert elicitation are involved in a variety of extension activities for dairy farmers and processors and have extensive experience in the quality and safety of milk and dairy products. Some of the key costs considered for these interventions include consultant costs, downtime, and labor costs (more details in Table 3). For intervention (iv), the addition of temperature sensor to half gallon packaging, the key cost considered was the cost of each individual sensor for each half gallon. For intervention (v), the application of antimicrobial coating to the floor drains intervention, the key costs considered were the cost of the coating for the floors, the downtime required, and the time required between reapplication of a new coating (Table 3.2). The total cost for the floor depreciation was calculated based on a $48,000 loan over 10 years with an interest rate of 5%. Based on the data collected, the (i) seek and destroy intervention would require the most labor. Even though it appears that the majority of the work will be done by the consultant and a third-party testing lab, the processing plant will be responsible for implementing interventions recommended by the consultant to identify and eradicate the problematic strain. The intervention with the least amount of labor but the most expensive implementation costs is (iv) the addition of temperature sensors to half gallon packaging.

Table 3.2. Estimated costs of interventions for a 6,000 sq ft plant with 6-7 production lines and 25 drains in total

Intervention	**Key costs considered**	**Low end**	**Mean**	**High end**	**Sample size**[1]
(i) Seek and destroy	1. Total cost for consultant for designated time period 2. Total cost for current sponge sampling and lab testing costs 3. Total cost for vector sampling and lab testing costs 4. Total cost for subtyping and identifying problematic isolate	$ 2,000	$ 12,500	$ 137,500	**n=4**
(ii) Improved preventative maintenance (PM) procedures	1. Current material costs for equipment part replacement (e.g. O-rings, gaskets, mesh screens, rubber fittings) 2. Labor costs 3. Downtime	$ 56,667	$ 80,000	$ 125,000	**n=3**
(iii) Increase periodic equipment cleaning (PEC)	1. Labor costs 2. Current cost of cleaning and sanitizer use 3. Downtime for periodic equipment cleaning 4. Cost of new filler nozzles	$ 25,667	$ 35,000	$ 50,000	**n=3**
(iv) Addition of temperature sensor to half gallon packaging	1. Material costs for time temperature indicators for 25,150,781 containers per year	$ 754,523	$ 23,641,734	$ 47,283,469	**n=5**

(v) Application of antimicrobial coating to floor drains	1. Cost of coating for floors ($/ sq ft) 2. Downtime required 3. Time required between reapplication of new coating	$ 68,000	$ 85,400	$ 91,500	**n=3**

[1]sample size refers to the number of experts that provided cost estimates

Price premium data

Retail prices and product information for a sample of half-gallon milk products (n=54) were collected in store and online in September 2020 from Stop & Shop (Brooklyn, NY), Wegmans (Ithaca, NY and online), Key Food (online), and Acme (online). In addition to retail prices, we collected product information on organic status, milk fat percentage, and pasteurization method (Table 3.3). The sample of milk products had the following qualities: organic (n=33) or conventional (n=21); 2% reduced fat (n=17), 1% low fat (n=11), whole milk (n=16), or fat free (n=10); and ultra-pasteurized (UP) (n=25) or high-temperature, short-time (HTST) (n=29). For analysis, we use the different fluid heat treatment processes to proxy shelf-life (Chapman et al., 2001): the shelf-life of ultra-pasteurized milk and HTST milk was assumed to be 90 days and 21 days, respectively.

Table 3.3. Milk price summary statistics

Characteristic	N=54[1]
Format	
In store	23 (43%)
Online	31 (57%)
Store	
A	16 (30%)
B	17 (31%)
C	14 (26%)
D	7 (13%)
Type	
Conventional	21 (39%)
Organic	33 (61%)
Product	
1% Low Fat Milk	11 (20%)
2% Reduced Fat Milk	17 (31%)
Fat Free Milk	10 (19%)
Whole Milk	16 (30%)
Processing	
High Temperature Short Time	29 (54%)
Ultra-pasteurized	25 (46%)
Mean Price (SD)	4.09 (1.37)

[1]N(%)

Environmental benefit data

The amount of milk consumed per capita, including milk consumers and non-milk consumers, is 141 pounds each year (USDA 2020), which equates to approximately 5.70 fluid oz per day. In the US, dairy is the primary source of protein for 58% of households (FMI and Nielsen, 2017). Thus, the amount of milk consumed per capita for consumers who get a majority of their daily protein from milk (i.e. milk consumers) was assumed to be approximately 9.82 fluid oz per day. The average global greenhouse gas emission for milk including production, processing, and transport has been estimated to be 2.4 kg CO_2e per kg of milk (FAO, 2010), which amounts to 0.000725 metric ton CO_2e per 9.82 fluid oz per day.

To determine the social benefit of each intervention strategy, we use the cost figure developed by the Interagency Working Group (IWG) which based the social cost of carbon values from three integrated assessment models at discount rates of 2.5%, 3%, and 5% (IWG, 2016). The social cost of CO_2 in 2020 using the 2.5%, 3%, and 5% discount rate was estimated as $62, $42, and $12 of 2007 dollars per metric ton of CO_2, respectively (EPA, 2016). Thus, using the previously calculated greenhouse gas emissions for milk per day (i.e. 0.000725 metric ton CO_2e per 9.82 fluid oz per day), the per capita social benefit of reduced CO_2e from potential avoided waste associated with an additional day of shelf-life for fluid milk, using the 2.5%, 3%, and 5% discount rate, is $0.04, $0.03, and $0.01, respectively. These figures will ultimately be used to determine the social benefit of implementing each of the five interventions.

Methodology

The empirical methodology is divided into three sections: (i) shelf-life estimation, (ii) hedonic price regressions, and (iii) cost-benefit analysis. First, we estimated changes in shelf-life attributed to each intervention. Then we estimated price premiums for an additional day of shelf-life. Lastly, we use results from (i) and (ii) with the environmental benefit data to evaluate the overall cost effectiveness of each intervention strategy.

Shelf-life estimation

The shelf-life estimation when applying each intervention is based on the previously developed microbial spoilage model in Lau et al. (2022), which predicts the spoilage of fluid milk by psychrotolerant Gram-negative bacteria introduced as post-pasteurization contamination. This model uses the percentage of half-gallons that reached a microbial threshold that assures compliance with the US Pasteurized Milk Ordinance limits for pasteurized milk (20,000 CFU/mL) by day 7 in the baseline model to estimate the shelf-life extension for each of the five interventions. In the model, 33.94% of half-gallons reached this threshold on day 7 and thus, each intervention was evaluated relative to this to determine the amount of storage time to reach a point where 33.94% of containers have >20,000 CFU/mL. More details on other aspects of the model parameterization are detailed in Lau et al. (2022).

Price regressions

Hedonic pricing models have a long history and were first introduced by Rosen (1974), who postulated that the monetary value of a product is derived from the specific prices associated with each of its attributes. This method has been used to determine agricultural land value (e.g. Bastian et al., 2002, Snyder et al., 2007) and to study the price structure of various agricultural products such as eggs or rice (Chang et al., 2010, Ndindeng et al., 2021). Because products are differentiated by their characteristics, Rosen's (1974) approach allows us to parse out the value of each product attribute. In this study, we used the hedonic pricing approach to determine the value of attributes associated with fluid milk.

Using the price premium data (Table 3.3), we specified five linear hedonic models of increasing of complexity to estimate the value of each product attribute commonly found for fluid milk. The interactions and variables we considered for the cost of fluid milk include market channel of the product (i.e. online or in-store), production type (i.e. organic or conventional), milk fat (i.e. whole milk, fat free milk, 1% low fat, and 2% reduced fat), and processing (i.e. HTST or ultra-pasteurization).

The model is determined by the following equation:

(1) $$P = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_5 x_5 + \varepsilon$$

here P is the observed retail price of fluid milk, B_0 is the intercept, x_1 to x_5 are the previously described milk product attributes, and ε is a normally distributed error term. We estimate five different specifications of equation (1) using Ordinary Least Squares (OLS) regression. For each model, B_0 represents a 1% conventional, low fat milk purchase in-store. With Model 1, simple linear regression was used to test if shelf-life significantly predicted the price with x_1 representing the shelf-life variable. With each model, we included additional interaction terms to determine the value of those attributes to parse out the true value of shelf-life. With Model 2, x_2 is the online channel dummy variable to evaluate a possible change in the value of shelf-life with the addition of online versus in-store channel attribute. With Model 3, x_3 is the organic dummy variable to determine the difference in price between organic and conventional fluid milk. In Model 4, we excluded the shelf-life variable (x_1) and use x_4 as a dummy variable for ultra-pasteurized processing. We then calculated the value of an additional day of shelf-life by dividing the coefficient estimate $\widehat{\beta_4}$ by 69, the difference in days between the shelf-life of HTST milk (i.e. 21 days) and ultra-pasteurized milk (i.e. 90 days). To assess the value of 2% reduced fat, fat free, and whole milk attributes, we include x_5 as a milk fat factor variable in Model 5. Similar to Model 4, in Model 5, we used the coefficient estimate for ultra-pasteurized dummy variable to determine the value of shelf-life.

Cost-benefit analysis

The costs considered in this analysis are described in the intervention cost data (Table 3.2). Both the private (firm) and social (environmental) benefits were considered in the analysis (Table 3.4). The private benefit is the value of each additional day of shelf-life calculated previously with the hedonic price regression. The environmental benefit is the social cost of carbon for each additional day of shelf-life. For interventions (i)-(iii), there was a range for the additional days of shelf-life each intervention provides (depending on the level of implementation; see Table 3.4) and thus there is a lower and upper bound for the benefits and costs of these interventions. To calculate the net benefit of each intervention, we took two approaches; one approach only considered the private benefit of implementing the intervention and the second approach accounted for both the private and social benefit of implementing the intervention. For the first approach, we subtracted the cost of implementing the intervention from the private benefit. For the second approach, we added the private and social benefit and subtracted the cost of the intervention.

Table 3.4. Total benefits and costs per half-gallon of fluid milk

Intervention	Days of extra shelf-life	Private Benefit per ½ gallon[1]	Social Benefit per ½ gallon[2]	Cost of Intervention[3]	Net private gain per ½ gallon (Private benefit - Cost of Intervention)	Net private and social gain per ½ gallon (Private + Social Benefit – Cost of Intervention)
(i) Seek and destroy	1-2	$ 0.03-0.06	$ 0.02-0.04	$ 0.00008-0.00547	$ 0.02-0.06	$ 0.04-0.09
(ii) Improved preventative maintenance (PM) procedures	2-7	$ 0.06-0.20	$ 0.04-0.13	$ 0.00225-0.00497	$ 0.05-0.19	$ 0.09-0.33
(iii) Increase periodic equipment cleaning (PEC)	6-7	$ 0.17-0.20	$ 0.12-0.13	$ 0.00102-0.00199	$ 0.17-0.19	$ 0.28-0.33
(iv) Addition of temperature sensor to half gallon packaging	2	$ 0.06	$ 0.04	$ 0.03-1.88	$ (1.82)-0.03	$ (1.79)-0.06
(v) Application of antimicrobial coating to floor drains	1	$ 0.03	$ 0.02	$ 0.00270-0.00364	$ 0.02-0.03	$0.04

[1]The value of each additional day of shelf-life was assumed to be $0.03 per ½ gallon; this was based on the hedonic pricing

approach detailed in the manuscript
[2]The social cost of CO_2e for each additional day of shelf-life using the discount rate of 3%
[3]The estimated cost of implementing each intervention strategy using expert elicitation and supplier quotes (see Table 2 for details)

RESULTS AND DISCUSSION

Estimation of fluid milk shelf-life extension that may be achieve by different interventions

The five interventions evaluated here were predicted to extend fluid shelf-life by between 1 and 7 days (Table 3.4). The two interventions that were predicted to allow for the largest shelf-life extension were intervention (ii), improved preventative maintenance, and intervention (iii), increase periodic equipment cleaning (PEC). The other three interventions (i, iv, and v; see Table 3.4) modelled were estimated to only allow for 1 – 2 days of shelf-life extension. For intervention (ii), the range of shelf-life extension varied substantially (2 – 7 days), based on the estimated effectiveness, which was 1 $\log_{10}$ reduction and 3 $\log_{10}$ reduction for the two levels of this interventions that were modeled. Our results further support previous studies that suggested that feasible interventions for extending fluid milk shelf-life include regularly scheduled preventative maintenance interventions or improving sanitary equipment and plant design (Reichler et al., 2020, Murphy et al., 2021). In addition to our work here, Buehler et al. (2018) previously evaluated different practical interventions to extend the shelf-life of milk, focusing however on shelf-life issues due to growth of sporeforming bacteria introduced with raw milk; in this previous study the developed model predicted that adjusting the temperature storage from 6°C to 4°C extended average shelf-life by 9 days. While combined this study and our study reported here suggest that substantial shelf-life extension of HTST milk is possible, future development of models that simultaneously simulate the impact of microbial raw milk quality and post-pasteurization contamination are needed to further facilitate industry decision making.

While we modeled a select few interventions that are relevant to fluid milk shelf-life extension, there is a growing body of research that examines the use of different interventions to improve the quality of perishable goods resulting in shelf-life extension. For example, strategies such as the use of high-pressure processing, pulsed light application and cold plasma-mediated treatments have been explored to extend the shelf-life of perishable goods such as produce (Pan et al., 2019). Active packaging and modified atmosphere packaging are also interventions that have been used to extend the shelf-life of products (Rodriguez-Aguilera and Oliveira, 2009). While a number of available technologies may not be practically or economically feasible for fluid milk, the approaches used here are valuable to evaluating different shelf-life extension strategies for a range of dairy products.

While one may argue that the estimated shelf-life extension for some interventions (e.g., those estimated to only yield extensions of 1- 2 days) are small and may have minimal practical value, one must be aware that managing perishable items compared to items that have longer shelf-life poses a different challenge. With perishable items such as fluid milk, which has an average of 17 days of shelf-life, an additional 1 day of shelf-life (e.g., from an intervention such as an application of antimicrobial coating to the floor drains) can still provide a substantial value to a firm. From a supply chain management point of view, extension of shelf-life allows for reduction in production and delivery lead times and can increase the stability of supply logistics (Cavaliere and Ventura, 2018, Akkas and Gaur, 2021). For consumers, products with a longer shelf-life would add a convenience attribute by allowing for fewer trips to the supermarket. Unlike other perishable products, consumers cannot use appearance as an extrinsic cue to evaluate the intrinsic quality of fluid milk (Aschemann-Witzel et al., 2015) and thus must rely on the printed best-by date. Therefore, the ability to apply the interventions that extend shelf-life for 1 to 7 days may offer substantial benefits.

Estimation of price premiums for fluid milk with extended shelf lives

When retailers are purchasing perishable goods such as fluid milk from suppliers or when consumers are purchasing product from the retail store, they must consider the likelihood that the product will spoil before it is fully consumed and thus there is a value associated with each day of shelf-life. In order to assess this value (and hence the value of fluid milk shelf-life extension), we performed price premium regressions. Fluid milk price data collected for this effort included more organic half-gallon samples (61%) than conventional half-gallon samples (39%). The sample of half-gallon milk products were roughly evenly distributed between HTST (54%) and ultra-pasteurized processing (46%) and between in-store (43%) and online channel (57%). On average the price of the half-gallon samples was $4.09 (SD=$1.37). Using these data, we used five models to determine the value of shelf-life, each with increased complexity. From these models, the coefficient estimates for the shelf-life variable and ultra-pasteurized variable were used to determine the value of shelf-life. Model 1 to 3 suggests that the value of shelf-life is $0.03 per day (Table 3.5). For Models 4 to 5, the estimated coefficient for the ultra-pasteurized milk indicator represents the total value of an additional 69 days of shelf-life. By dividing the value of ultra-pasteurized milk processing over 69 days, we also estimated the value of shelf-life to be $0.03 per day. The fact that the value of an added day of shelf-life was estimated to be $0.03 across each of the five models indicates that our main results are robust to changes in specifications. In addition, the estimated value of $0.03 for each additional day of fluid milk shelf-life, is similar in magnitude with that of Tsiros and Heilman (Tsiros and Heilman, 2005), who used a mixed effect model that investigated the willingness to pay (WTP) for milk as the number of days left before the product's expiration decreases and estimated WTP of $0.04 per day.

Table 3.5. Price regressions

	Model 1[1]		Model 2[2]		Model 3[3]		Model 4[4]		Model 5[5]	
Variables	B[6]	SE B[7]	B	SE B	B	SE B	B	SE B	B	SE B
1% Low fat Milk	2.30	0.18	2.05	0.22	1.98	0.22	2.57	0.20	2.50	0.27
Shelf-life	0.03	0.00	0.03	0.00	0.03	0.00				
Online			0.35	0.19	0.41	0.19	0.41	0.19	0.42	0.19
Organic					0.61	0.28	0.61	0.28	0.63	0.29
Ultra-pasteurized							1.96	0.27	1.93	0.28
2% Reduced Fat Milk									0.17	0.27
Fat Free Milk									-0.06	0.30
Whole Milk									0.10	0.27

[1]Simple linear regression with the intercept representing a 1% conventional, low fat milk purchase in-store with a shelf-life variable
[2]Model 2 represents Model 1 with the addition of an online channel dummy variable
[3]Model 3 represents Model 2 with the addition of an organic dummy variable
[4]Model 4 represents Model 3 with the exclusion of the shelf-life variable and the addition of a dummy variable for ultra-pasteurized processing
[5]Model 5 represents Model 4 with the addition of milk fat variable
[6]Unstandardized beta; represents the slope of the line between the predictor variable and the dependent variable
[7]Standard error for the unstandardized beta

Our data on the value of shelf-life extension of HTST milk are important as dairy products represent a unique challenge within grocery stores because they have logistical requirements such as temperature control and a perishable nature and therefore must be purchased frequently (Reiner et al., 2013). In addition to its unique challenges, there are no direct alternatives to HTST fluid milk from a sensory profile, either. While consumers can opt to buy milk with different processing technologies such as ultra-pasteurized (UP) milk for extended shelf-life, an important criterion affecting consumer acceptance is flavor (Kühn et al., 2006). Because UP milks are processed at a higher temperature compared to HTST milks, UP milks have a distinct cooked and sulfur flavor profile which may not be favorable to some consumers (Lee et al., 2017, Jo et al., 2018). Data on the value of extended shelf-life of HTST milk thus will help industry with decision making on the economic value of further development of "Extended Shelf-life" (ESL) HTST fluid milk products.

There exists a large literature in the field of markdown management, some of which suggests markdowns as a recommended tactic to increase sales and prevent products from become unsaleable (GMA-FMI, 2008). However, while applying a discount may be a strategy to promote the sale of aging products, this is not applicable to products that already have a low-margin such as milk. Offering a discount can result in a new pool of customers who only want the old product and can cause an increase in ordering from the retail store (Chua et al., 2017). In addition, determining the optimal discounting for products would require a large investment from retailers (e.g. analysis of profit margins for each product, evaluation of the effect of discounting on the specific product, cross category effects, etc.) (Wang and Li, 2012). Discounting milk can also be detrimental since there have been numerous studies showing that the price of a product serves as an indicator of quality perception for consumers (e.g. Monroe, 1973, Gneezy et al., 2014), and consumers' quality perception of the product decreases with markdown (Hariss et al., 2020). Thus, discounting may not be a profitable strategy for products similar to milk, whereas extending the shelf-life of products may be a better tactic that allows the firm to maintain the full value of the product for a longer period of time.

Cost-benefit analysis (CBA) for different interventions that increase fluid milk shelf-life

The private and social benefits for four of the five interventions (i.e. interventions i, ii, iii, and v) evaluated here were consistently estimated with a net gain when considering either only private benefits (range of \$0.02 – 0.19 per half-gallon; see Table 3.4) or both private and social benefits (range of \$0.04 – 0.33 per half-gallon; see Table 3.4). Interventions (ii), improving preventative maintenance (PM) procedures, and (iii), increased periodic equipment cleaning, which both provided for substantial shelf-life extensions (2 – 7 days), showed the largest impact on net private gain (\$0.05 to 0.19 and \$0.17 – 0.19, respectively), and net private and social gain (\$0.09 to 0.33 and \$0.28 – 0.33, respectively). The estimates for total cost of implementing intervention (ii) ranged from \$56,667 to \$125,000, resulting in a cost of \$0.00225 to \$0.00497 per half-gallon, while the estimates for total cost of implementing intervention (iii) ranged from \$25,667 to \$50,000, which equates to between \$0.00102 and \$0.00199 per half-gallon of milk.

Interventions (i), implementing seek and destroy, and (v), application of antimicrobial coating to floor drains, had lower estimated net private gain (\$0.02 to 0.06 and \$0.02 – 0.03, respectively) and net private and social gains (\$0.04 to 0.09 and \$0.04, respectively). The total costs of implementing intervention (i) were estimated to be between \$2,000 and \$137,500. This was treated as an annual cost (as it is likely that this would have to repeated yearly as new issues that need to be addressed with seek and destroy are expected to occur at a set frequency, which we assumed was annually); this cost equates to between $0.00008 and $0.00547 per half gallon. The total costs of implementing intervention (v) were estimated to be between $68,000 and $91,500, which equates to between $0.00270 and 0.00364 per half-gallon.

Intervention (iv), the addition of temperature sensor to half gallon packaging, was estimated to be the least cost-effective measure with net private gain estimates ranging from -$1.82 to +$0.03, net private gain estimates ranging from -$1.79 to +$0.06 and estimated costs ranging from $0.03 and $1.88 per half-gallon (Table 3.4). Of the five suppliers that were contacted for a quote on the temperature sensors, only one supplier provided a price (i.e., $0.03 per sensor) that would allow for a net gain. As a result, when implementing this intervention, there is a net loss per half gallon of milk when looking at the high end of the potential costs. These data suggest that reliable low-cost sensors would be needed before this intervention is competitive for fluid milk shelf-life extension.

Overall, our data suggest that a number of interventions that will increase fluid milk shelf-life will result in a net gain when considering either only private or both private and social benefits, assuming that a price premium of $0.03 per half gallon of milk can be realized and assuming that our cost estimates are appropriate. Given that consumers value shelf-life in fluid milk products, it appears likely that there would at least be an opportunity to pass on the cost for implementing these interventions to consumers through retail pricing in stores, even if the full $0.03 premium may not be achievable. While milk is currently differentiated based on milk fat percentage, price, and conventional versus organic, this provides an opportunity for firms to use the shelf-life attribute to compete in horizontal product differentiation. Grebitus et al. (2013) conducted a survey that showed that consumers were willing to pay for longer shelf-life in ground beef as long as the product was safe, and they understood the technology. Cavaliere and Ventura (2018) furthermore showed that consumers will accept technology that extends shelf-life if they have a high level of food knowledge. Montero et al. (2021) show that convenience-oriented consumers are willing to pay a premium for a ready to eat meal with an extended shelf-life. Thus, consumers are receptive to paying extra for a product with longer shelf-life.

Fluid milk's impact on food waste is substantial as this product makes up 31% of dairy products expenditure in US households in 2020 and was the sixth most consumed beverage in the United States in 2020 (Bureau of Labor Statistics 2021; Beverage Marketing Corporation 2020). Hence extending the shelf-life of fluid milk would not only provide significant benefits to firms but would also provide substantial environmental benefits. Environmental benefits of fluid milk shelf-life extension may be particularly valuable since there has been increasing industry attention and pressure to address the challenge of food waste. If a company could credibly signal that their milk products are more environmentally friendly, this type of information disclosure would enhance product differentiation, relax price competition, and therefore allow firms to charge more for the fluid milk (Shaked and Sutton, 1982). On the retail end, when product is not able to be sold, a large portion of the product is sent to landfills or incinerator, which further increases air pollution and greenhouse gas emissions (Bloom, 2010). The environmental impact of food consumption is another significant consumer concern that ultimately shapes their food purchasing behavior (Moser, 2015). Corporate environmental, social, and governance (ESG) initiatives now shape consumer choice as well as institutional investment decisions (Kim et al., 2021). Companies are actively pursuing sustainability as a strategy in order to attract and retain their customer base and to remain competitive among other businesses (Du et al., 2007, Oláh et al., 2019). Consumers are interested in corporate social responsibility (CSR) initiatives of companies and the impact on the environment is one of the many factors they use to assess a company (Bhattacharya and Sen, 2004, Du et al., 2007, Rodrigues and Borges, 2015). Indeed, companies that display an environmental orientation and a commitment to the environment are associated with greater profit and market share (Menguc and Ozanne, 2005).

Study limitations and opportunities for future studies

While the cost benefit analysis conducted here provide insights on the economic and environmental impact of various intervention strategies that could be used to extend fluid milk shelf-life, there are several limitations that should be addressed in future studies. One limitation of this analysis is the costs and benefits are based on predicted shelf-life extensions obtained with a spoilage simulation model and are also based on cost estimates. For more reliable data, interventions would need to be performed (or at least piloted) in a processing plant (with appropriate cost accounting) in order to obtain "real world" data on intervention costs and the additional days of shelf-life a given intervention can provide. However, use of previously developed shelf-life prediction models, including the model used here (Buehler et al., 2018, Lau et al., 2022), along with the cost-benefit analysis conducted here can already facilitate plant-level decision making, by enabling processors to perform an initial assessment of interventions most likely to be cost-effective. It is however important to recognize that implementation costs will vary depending on the processing plant size and a firm's specific situation and that initial feasibility assessments may need to use different cost estimates than those used here.

Another limitation of the study reported here is that the implementation of the five interventions was evaluated independently, which helps processors make a choice between discrete interventions. However, we understand that processing plants may want to implement multiple interventions simultaneously. Evaluation of multiple interventions implemented simultaneously, however, presents significant challenges from a modeling standpoint, as some of these interventions (i.e. seek and destroy intervention and increased periodic equipment cleaning intervention) change the same model input (frequency) in the model.

In addition, there are several limitations in the evaluation of the value of shelf-life worth noting. There were two assumptions made: (i) there is a linear increase in the value of additional shelf-life between HTST and UP products and that (ii) the shelf-life of the HTST and UP products are 21 days and 90 days, respectively. In addition, the product information and prices collected for the evaluation of the value of shelf-life were based on a convenience sample of New York retail stores and therefore may not be representative of all regions in the U.S. While we believe that there are opportunities to further improve estimates on the value of added shelf-life for HTST fluid milk, our estimates of an added value of $0.03 per half gallon are in-line with previous estimates (Tsiros and Heilman, 2005), as detailed above.

CONCLUSIONS

Despite the growing literature in operations and logistics management to tackle the logistical aspects of food waste, for certain food products a significant opportunity exists to address this problem through the intrinsic nature of the product. This study explored how interventions applied at a dairy processing plant can extend the shelf-life of fluid milk, thereby reducing consumer-level food waste. Importantly, the types of interventions applied here were estimated to often provide both private and social benefits, suggesting that further work on improving the intrinsic nature of dairy products (e.g., shelf-life) may substantially benefit the dairy industry, both form an individual profitability standpoint as well as from a reputational standpoint, with regard to industry’s commitment to addressing food waste.

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CHAPTER 4

CONSUMER PERCEPTIONS OF QR CODE TECHNOLOGY FOR ENHANCED FLUID MILK SHELF-LIFE INFORMATION PROVISION IN A RETAIL SETTING

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ABSTRACT

There is increasing awareness of the impact of food waste and the large role best-by or sell-by dates play in consumer food waste. To address this issue, predictive models have been developed that can not only provide more accurate best-by dates for fluid milk but could also be used to dynamically predict shelf-life (e.g., based on distribution data such as storage temperatures) and adjust prices for products closer to the end of shelf-life. However, limited information is available on strategies to communicate this type of information to consumers. Here we assessed the consumer acceptance of (1) quick response (QR) code technology to communicate product shelf-life and (2) shelf-life dependent pricing based on QR codes by offering both half-gallon fluid milk with traditional printed best-by dates and identical products with QR codes to convey best-by dates over an 8-wk time period in a retail setting. Overall, 62% of half-gallon containers sold over this time frame featured QR codes and 48% of QR code scans were linked to subsequent sales, suggesting the possibility of substantial consumer acceptance of novel technologies to display and communicate best-by dates. Preliminary data based on a small number of sales also showed that consumers did purchase QR code-labeled products offered at a reduced price due to limited remaining shelf-life. Our data suggest that at least some consumer segments

would adopt QR code-based shelf-life labels, which presents an opportunity to better manage and communicate "best-by" dates and use dynamic pricing strategies to reduce food waste that occurs when an end-of-shelf-life product is either not sold or is discarded by consumers. Overall, QR codes represent a strategic opportunity for the dairy industry to achieve greater sustainability and to foster stronger connections with customers through enhanced provision of information that highlights sustainability practices implemented across the whole supply chain.

BODY

Environmental, social, and economic concerns have increased regarding food waste as nearly 1.3 billion tons of food have been reported to be lost or wasted globally every year (Gustavsson et al., 2011). Along the supply chain, the retail sector and consumers are estimated to be responsible for 31% of food waste (Buzby et al., 2014). Here, we refer to this as "food waste," consistent with the Food and Agriculture Organization of the United Nations (FAO) definition of food waste as "the decrease in quantity or quality of food resulting from decisions and actions by retailers, food services, and consumers" (FAO, 2019; p. 5). In 2010, dairy products were estimated to contribute to approximately 25.4 billion pounds of food waste at retail and consumer levels in the United States, with fluid milk making up of 32% of the dairy product waste (Buzby et al., 2014).

Even though food labeling can provide important information to consumers, in some cases it can also create confusion and therefore drive food waste. Importantly, there is limited regulatory guidance in the United States related to best-by dates and expiration dates (USDA Food Safety and Inspection Service, 2019), including the phrasing used (e.g., best-by; use-by), how the expected shelf-life should be determined, and even if date labeling is required, which can cause consumer uncertainty about interpretation of shelf-life labels (Hall-Phillips and Shah, 2017).

Indeed, Wilson et al. (2018) found that consumers differ in their interpretation of "best by" and "use by" dates and may misinterpret these terms. Roe et al. (2018) evaluated the discard rate of fluid milk of consumers and also found that consumer responses differed depending on whether they were given milk with or without date labels. When given milk without a date label, consumers were reliant on their senses to evaluate the milk and, thus, even when milk was past its sell-by date, there was a lower discard rate for these samples (Roe et al., 2018). On the other hand, even when milk that had 3 more days until its sell-by date, consumers were more likely to discard unspoiled milk with date labels present (Roe et al., 2018). While these authors concluded that innovative date labeling and education around date labels could reduce milk waste, we are not aware of published consumer studies that evaluated innovative date labeling approaches for milk in commercial retail establishments.

While one approach to address the confusion around date labels is the use of a standardized label such as a "best if used by" label (S.3324–Food Date Labeling Act of 2021; Congress.gov, 2021), technology-enabled solutions, such as quick response (QR) technology, offer a novel solution to address food waste and specifically address the best-by-date issue. For example, QR code labels coupled to a computer model that predicts shelf-life (i.e., best-by dates) of fluid milk using lot-specific input data would enable provision of more precise spoilage information to consumers, which could help reduce food waste that results from consumers discarding unspoiled milk prematurely.

QR codes were first developed for the auto industry to track manufacturing and distribution for car parts (Denso Wave, 2022) and have since been used in other industries such as education (Karia et al., 2019) and print media (Probst and Brokaw, 2012). There has been increasing movement to use such technology in the food industry, specifically for food traceability purposes (Kim and Woo, 2016). Despite the increased use of QR codes, there are a limited number of studies that specifically examine consumers perceptions of and willingness to use QR codes to access product information. One survey conducted in 2016 evaluated if consumers would purchase oysters with or without labels; data from this study showed that 52.6% of respondents would access labeling information through a QR code with a smartphone (Li and Messer, 2019). Kim and Woo (2016) analyzed consumers' intentions of using a QR code to understand the food traceability system, and their findings indicate that consumers have a positive attitude toward using QR codes as a tool. Furthermore, increased use of contactless payments and dining in response to the COVID-19 pandemic has greatly expanded the use of QR code technology by consumers (Zhong and Moon, 2022).

The purpose of this study was to evaluate consumers' acceptance of QR code technology and explore its use as a replacement for traditional best-by dates for dairy products. We conducted a 2-part pilot study in a university retail location that sells fluid milk and other dairy products. All research activities were reviewed by Cornell's Institutional Review Board for Human Participants (IRB) and were approved and granted exemption under protocol number IRB0143820. For phase 1 (wk 1–4), the objective was to first determine consumers' receptiveness to using QR code technology to access information about product shelf-life (using HTST-pasteurized fluid milk in half-gallon containers as a model). For phase 2 (wk 5–8), the objective was to determine if offering a discounted price schedule based on shelf-life for half-gallon fluid milk would (1) change consumers' willingness to use the QR code technology (relative to the phase 1 baseline) and (2) increase sales of milk nearing its best-by date thereby reducing potential food waste.

This pilot study took place at the Dairy Bar at Cornell University in Ithaca, New York, between January and March 2022. The Dairy Bar sells 3 different sizes of fluid milk products: individual (8 oz), half gallon, and quart. We used fluid milk in half-gallon containers as a model for this study as the smaller serving sizes (e.g., 8 oz and quart) are often consumed immediately or soon after purchase, possibly making product shelf-life a less important factor in purchase decisions. For phase 1 and phase 2 of the study, the half-gallon milk products were offered for purchase with 2 labels: (1) the traditional printed "best-by" date with no alteration to the half-gallon carton (referred to as "static label milk") and (2) a QR code that allowed consumers to access shelf-life information as well as (for phase 2 only) pricing information (referred to as "QR code milk"). For the QR code milk, the best-by date was concealed with white tape and replaced with a statement sticker. During phase 1 the sticker stated "Scan the QR code for the best-by date," and during phase 2 the sticker stated "Scan the QR code for a potential discount and best-by date." We disclose the discount first in the phase 2 label to help mitigate possible customer inattention when interacting with the label (Loewenstein et al., 2014). The QR code corresponding to the best-by date was placed on the upper left corner of the milk container above the existing product label (Figure 4.1A).

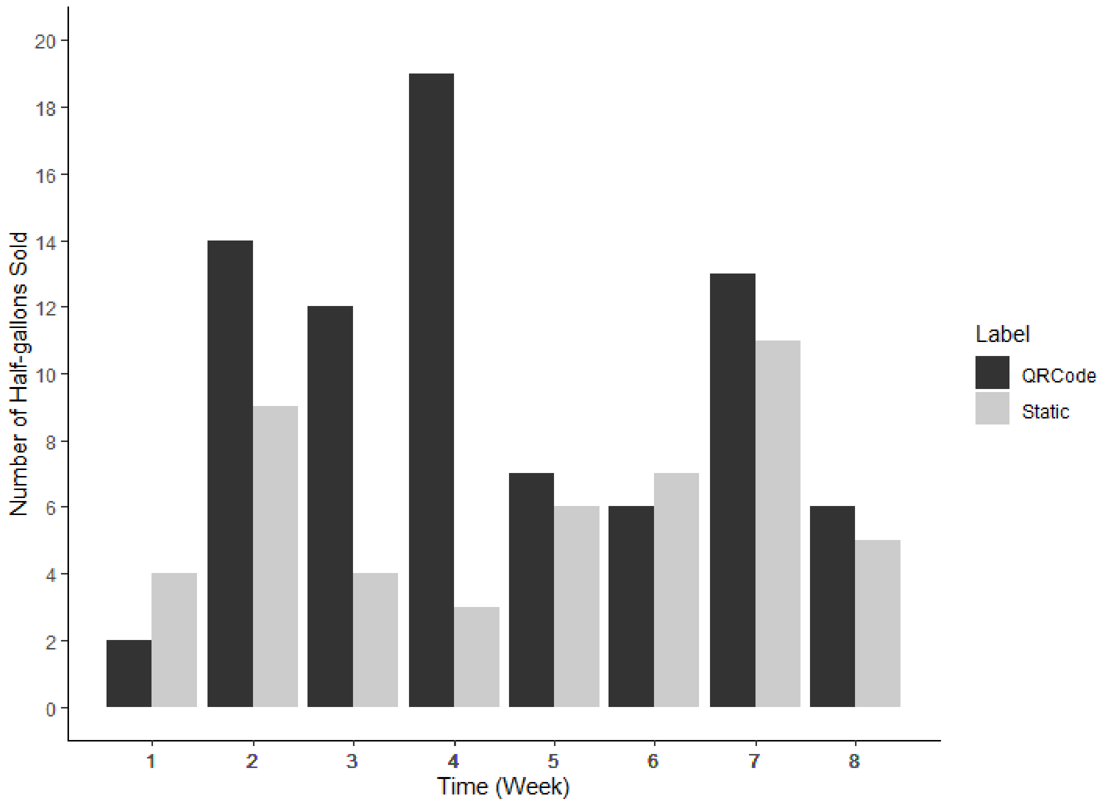
Figure 4.1. (A) Alterations done to the quick response (QR) code milk for phase 1 and phase 2. (B) Sign on the display case informing customers about the QR code label. (C) Directed website display following a customer scan of the QR code on the half-gallon. (D) Dairy Bar shelf set-up for the pilot study.

To control the variables in the pilot study, we placed the half-gallon milk products on the same shelf and maintained a shelf placement similar to what the Dairy Bar has used in the past. Historically, the Dairy Bar has 2 rows of each milk fat type (i.e., skim milk, reduced fat, whole milk) with 5 half-gallons per row; from left to right, the order of the half-gallon milks is skim milk, reduced fat, and whole milk. For this study, we maintained a total of 2 rows of each milk fat type, with the left 3 rows used to display static label milk and the right 3 rows used to display the QR code milk. The milk was placed in the following order: skim static label, reduced fat static label, whole static label, skim QR code, reduced fat QR code, and whole QR code (Figure 4.1C). Additional measures taken to control the variables of the study included a daily check (at the start of each day) to ensure that an equal number of half-gallons containers with static labels and QR codes were present. Stockouts never occurred during the duration of the study, and Dairy Bar employees were instructed to maintain at least 3 half-gallon containers of milk per row throughout the day and restock if necessary. Dairy Bar employees were also specifically instructed not to remove any of the half-gallon milks from the shelf until the end of the day of the printed best-by date.

To inform potential customers of the new QR code labels, we placed an 8.5″ by 11″ color sign on the front of each display case with instructions to scan the QR code on the half-gallon milk container to get the best-by date. There was also a statement on the bottom of the sign that stated, "Help reduce food waste by choosing the carton with a best-by date that best fits your needs." During phase 2 of the study, customers saw the same sign on the display case with the addition of a statement mentioning the potential discount and instructing them to show their screen to the cashier at checkout (see Figure 4.1B). For the QR code milk, the best-by date and price of the milk was communicated with the use of the QR code. During phase 1 of the study, when a customer scanned a QR code, it directed them to a website with a display that showed (1) the date and time at which the customer scanned the QR code, (2) the best-by date, and (3) a statement "Thank you for your contribution in helping reduce food waste." During phase 2 of the study, customers saw the same display with the addition of a shelf-life dependent price displayed below the best-by date and above the "thank you" statement (see Figure 4.1C). For phase 2, we used 4 different price levels: the original price (i.e., the same price displayed on the static label milk) and 3 discounted prices. The discounting schedule was determined based on the following information. From a previous paper, the mean milk consumption for milk consumers per capita was approximately 9.82 fluid oz per day (Lau et al., 2022b). A half-gallon is approximately 64 fluid ounces so an average milk consumer would finish a half-gallon milk in 7 d. We therefore assumed that consumers would not consider the possibility of spoilage or waste when buying a half-gallon of milk unless the best-by date was less than a week away. Thus, the discounting began when there was less than 7 d from the best-by date, and we subdivided that into 3 periods: 5 to 6 d, 3 to 4 d, and less than 3 d from the best-by date. For each price level, we doubled the discount rate such that greatest discount would be in the fourth price level. The corresponding discount rates were 10%, 20%, and 40%, with the final prices being $2.87, $2.55, and $1.91, respectively.

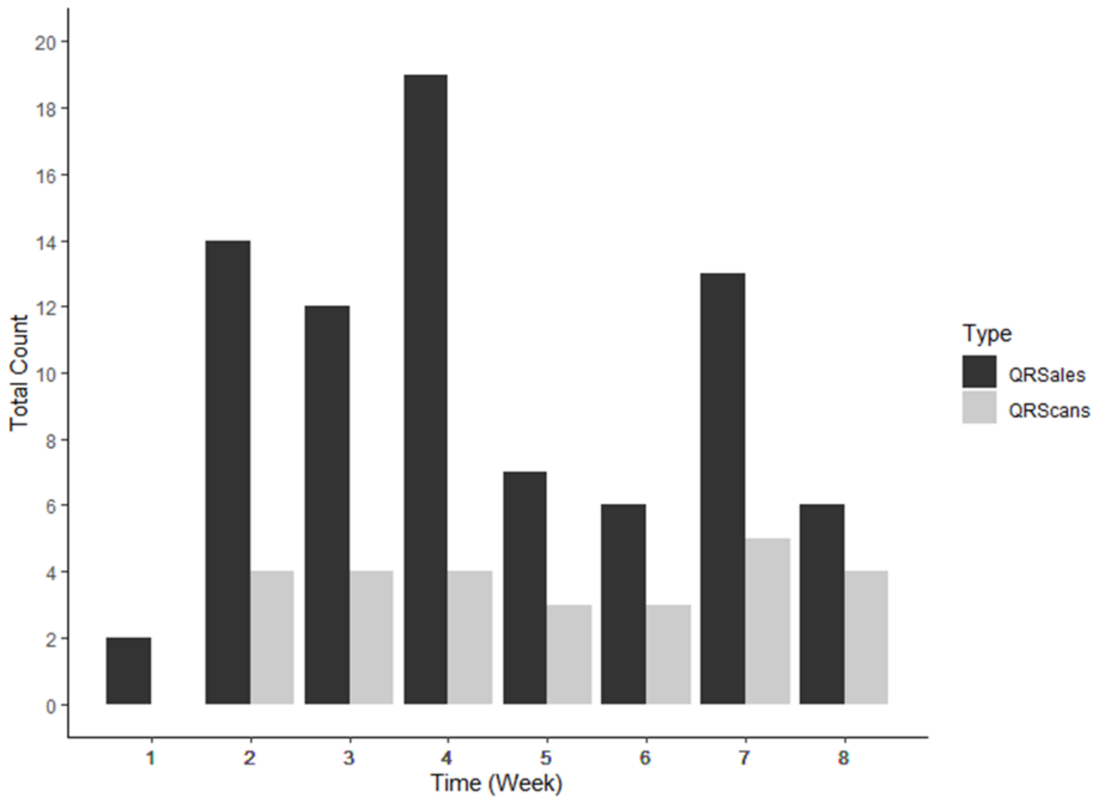
Overall, our study showed broad consumer acceptance of QR code-based shelf-life labeling of milk as 62% of product sales, or a total of 79 QR code milk sales, across the 8 wk were half-gallon containers with QR codes. The proportion of QR code sales was slightly lower in phase 2 (32/61 or 52% of sales) as compared with phase 1 (47/67 or 70% sales; see Figure 4.2 for details). This could indicate the existence of a novelty effect: as the novelty of the QR-code-based labeling "wore off," consumers were less interested in using QR codes. Studies suggest that consumers' perceptions of a new technology are strongest at the initial stages and will decay unless there is substantial variation between iterations of the technology (Hopp and Gangadharbatla, 2016). Similarly, it could be possible that the novelty of the waste reduction message could have worn off. The decreased proportion of QR code sales in phase 2 may also be an unintended consequence of dynamic pricing: The increased purchase complexity introduced in phase 2 (when discounts were implemented) may have deterred consumers from using the system, despite the potential savings.

Figure 4.2. Quantity sold of half-gallon containers of milk with quick response (QR) code labels and static date labels over the 8 wk of the study.



Interestingly, despite a substantial number of QR code milk sales, the number of customer QR code scans was consistently lower than the number of sales. The overall proportion of QR code scans to QR code sales was 34% (27 QR scans/79 QR code milk sales), and a lower number of QR code scans than QR code sales was observed for each of the 8 wk of our study (Figure 4.3). In addition to the number of half-gallon containers sold with QR codes, we were also able to identify transactions in which a single customer purchased more than one half-gallon container at a time. Among all QR code containers sold, we only identified one such transaction (in this case 2 QR code containers were purchased, as supported by 2 QR code sales at the same time, in hours and minutes). Therefore, the substantially lower number of QR code scans as compared with QR code sales cannot be explained by events in which a consumer purchased multiple QR code milk products but only scanned one QR code, possibly under the misconception that such information would be representative of all containers purchased.

Figure 4.3. Scans of quick response (QR) code labels for half-gallon milk containers compared with the quantity sold of half-gallon containers of milk with QR code labels over the 8 wk of the study.



The observation of a greater number of QR code sales compared with QR code scans indicates that some consumers opted to purchase QR code milk without scanning the QR code on the half-gallon container. One possible reason for this occurrence is the existence of perceived value and trust around the QR code label. Shin et al. (2012) showed that perceived interactivity, the ability of the QR code to provide information with minimum lag time, has an influence on the trust, behavior, and social support for consumers when using QR codes. Kim and Woo (2016) found both a positive effect on consumer attitudes in using QR codes and an understanding among consumers of the importance of QR codes in agriculture and food industries. Another possible explanation for this observation could be customer inattention. This is consistent with research that has shown that many consumers cannot recall the price of the items they placed in the shopping cart accurately or are inattentive to price changes (Dickson and Sawyer, 1990; Clerides and Courty, 2017). Despite the fact that signs were placed on both the retail refrigerator door and the half-gallon milk informing customers about the discount opportunity, customers may still have overlooked this information. Other possible reasons for the QR code scans and sales discrepancy may include a greater inherent trust of the half-gallon milk at this retail setting or that customers intended to drink the half-gallon milk in a period of time where the best-by date would not be of concern.

Despite the economic incentive offered in phase 2 of the pilot study, using the Mann-Whitney U test in R v 4.0.3 (R Core Team, 2020), there was no significant difference in the proportion of QR code scans ($P = 0.54$) or in the proportion of QR code sales ($P = 0.88$) between phase 1 and phase 2. Only 4 QR code milk sales from phase 2 of the study (12.5% of QR code sales during this phase) were purchased with a discount. It is important to note that the Dairy Bar staff was instructed to only apply a discount if the customer showed their phone screen to the cashier. Thus, some of the QR code milk sold may have qualified for a discount, but it may not have been applied due to a lack of customer participation. Customers also may not have taken advantage of the shelf-life dependent pricing in phase 2 of the study because of the additional effort required to scan each of the QR codes to determine the discount for each product. For example, Hansen et al. (2021) observed that having a reduced purchase price displayed on the shelf itself, without the need for customers to do additional work to determine the discount, was effective in increasing sales of aging item. They conducted a field study in a European grocery retail store that used electronic shelf label price tags and barcodes to facilitate price discounts of perishable products (e.g., breaded chicken, raw chicken, pre-cooked dishes) closer to the end of shelf-life. Even though the discounts increased the sales of aging items, they did find that the "hassle cost" of having to check multiple sell-by dates plays a role in customer purchase decisions. For example, when there were fewer items on the shelf, customers would choose the newer product due to a decreased hassle cost of inspecting all the products (Hansen et al., 2021). Overall, these findings suggest that dynamic shelf-life based pricing can increase sales of aging products, but the hassle costs of having to scan multiple packages to identify discounted products may impede its acceptance by consumers, particularly for low-cost items.

As our study collected separate time stamps for both QR code sales and QR code scans, we used these data to identify QR code scans that led to actual sales. We assumed that the sale of a QR code milk product within 5 min of scanning a particular QR code represented sales of that scanned product, which suggests that 48% (13/27) of QR code scans led to QR code milk sales. Conversely, this implies that 52% (14/27) of QR code scans did not lead to a subsequent sale, suggesting the need for follow-up studies to assess why some QR scans do not convert to sales.

Our study provides valuable initial evidence that some consumer segments are likely to accept QR code technology, which supports the potential of broader use of QR codes to provide information such as the best-by date in retail settings. This finding is also supported by at least one previous study that indicates that customers will pursue additional information about a product through a QR code (Li and Messer, 2019). Nonetheless, the customer base in our study (predominantly younger college students, as well as faculty and possibly university employees) may be more willing to use these technologies (and may be more concerned about food waste reduction) than the general public. Due to the nature of our study, we were unable to collect individual sociodemographic information to explore these potentially confounding factors. Substantial additional work is therefore needed in this area to confirm our results and explain those nuances. In particular, future studies in traditional retail setting with different customer segments are necessary to further characterize consumer reception to QR code technology for providing shelf-life related information. Importantly, our study also reinforces the need for further development of models that predict fluid milk shelf-life (Buehler et al., 2018; Lau et al., 2022a), as these models will be needed to provide dynamic shelf-life information that can be disclosed via QR codes.

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CHAPTER 5

THE EFFECTS OF POOR FLUID MILK EXPERIENCE ON STORE CHOICE AND CUSTOMER LOYALTY IN DIFFERENT MARKET CHANNELS

ABSTRACT

As there has been increasing consumer demand for high quality food products, it is essential that retail stores and manufacturing plants produce such products to ensure a positive customer experience. In the fluid milk industry, dairy processors have worked extensively to address bacteria that can have detrimental effects on flavor, appearance, and odor and have used comprehensive detection and diagnostic tools to ensure they produce high quality milk. While there have been extensive studies on how poor fluid milk quality can lead to negative consumer sensory acceptance, there is limited information on how a poor experience with milk, which can include negative sensory acceptance, can influence consumer choice in brick-and-mortar and online retail settings. This has important marketing implications because the product experience directly affects customer satisfaction, and studies have shown that increased customer satisfaction has been associated with repeat purchases, customer retention, and increased sales. In this study, we assessed how a poor experience with fluid milk can affect consumer grocery purchasing behavior in a particular market channel (in-store and online-mediated in-store). We find that a poor experience with milk is associated with a greater likelihood of switching retail stores and with lower reported net promoter scores, which suggests that having high quality milk may help retailers improve customer loyalty. Overall, our work highlights the important role that higher quality fluid milk products can play in driving store choice and customer loyalty in retail settings.

INTRODUCTION

There have been countless studies showing the importance of consumer perception of food quality and the role it plays in purchase and consumption decisions. A negative influence on consumers' perceptions can occur at the point of purchase (e.g., search attributes such as visual external defects) or after ingesting the product (e.g., experience attributes such as poor sensory experience due to spoiled product). Consequences of poor experiences with a given product may include (i) customers dissatisfaction that not only reduces purchase of a specific brand but also a brand category, (ii) diminished customer loyalty to a retail chain or a distribution channel (e.g., Instacart) and (iii) reduction in a product's market share (Rust and Zahorik, 1993).

While evaluating customer satisfaction and the implications it can have on the retail store can be challenging, this information is important to allow retailers to make decisions on the value of improved food quality. Current measures of customer satisfaction include the use of the American Customers Satisfaction Index, SERVQUAL and net promoter score (NPS) (Parasuraman et al., 1988, Anderson and Fornell, 2000, Reichheld, 2003). However, none of these approaches, to our knowledge, have been used to assess how a poor experience with a food product (e.g., due to spoilage) can influence customer retention and likelihood of repurchase. Improved information on the value to consumers of products that meet quality and shelf-life expectations thus will help ensure appropriate investments by retailers in products that show improved quality and extended shelf life. Information on the benefits to retailers and eCommerce vendors of offering perishable food products with higher quality and extended shelf life can also play an important role in helping retailers focus on maintaining their attractiveness to existing and new customers, as a negative experience with a specific perishable food (e.g., milk, fresh produce) may reduce purchase volume, shopping frequency, or store patronage all-together at the retailer where that product was purchased.

While there are number of perishable fresh products that can easily spoil and create negative customer experiences (e.g., fresh produce, some seafood, fluid milk, fresh cheese), we chose fluid milk as a model system as anecdotal information suggests the consumer complaints about fluid milk spoilage and off-flavors are commonly provided to retailers. In addition, there is an increasing number of simulation and trade-off models (Buehler et al., 2018, Enayaty-Ahangar et al., 2021, Lau et al., 2022) that will allow industry to assess the impacts and costs of different interventions that can enhance fluid milk shelf life and quality. These models provide an important starting point for rational business decision making for investments that can extend fluid milk shelf life. However, the lack of information on the value of extended fluid milk shelf life and reduced spoilage (for both fluid milk producers and retailers) impedes the ability of producers to fully assess the financial benefits of these product enhancements, potentially preventing such investments that could also have positive environmental consequences by reducing food waste.

MATERIALS AND METHODS

Survey design

An online survey was designed in Qualtrics and administered in the winter of 2022 in the United States through the Prolific platform (Prolific, 2022). All research activities were reviewed by Cornell University Institutional Review Board for Human Participants (IRB) and have been approved and granted exemption under protocol number IRB0143820.

The survey was split into three parts. The first part of the survey asked participants questions about their purchase behavior for dairy milk including store format, purchase frequency, consumption frequency, type of milk, milk size, and perception of a poor experience. The second part of the survey posed hypothetical questions to the participants about how purchasing milk in-store or online and whether they had a good or poor experience would affect their likelihood of returning to same store to buy fluid milk again and their likelihood to recommend the store to a friend or colleague. Finally, the third part of the survey asked respondents demographic questions regarding their age, household, education level, gender, income, marital status, ethnicity, and state of residency. A complete copy of the survey is included in online supplementary material Appendix A.

Survey administration

We piloted the survey with 50 respondents on March 28, 2022, with a compensation of $2.00 for each completed response. We expected the survey to take 10 minutes to complete, for an effective compensation rate of $12.00 per hour. In reality, the average response time was about five minutes. Importantly, we did include two attention check questions in the survey to ensure valid participant responses. Respondents were eligible to take part in the survey if they met six prescreening requirements: (i) Respondents taking the survey must not be a student, (ii) respondents' country of residence must be the United States, (iii) respondents must not be following a vegan diet or dietary restriction, (iv) respondents must be the main or shared grocery shopper for the household, (v) respondents must have purchased or currently purchase groceries online, and (vi) respondents must not have a dairy/lactose-free dietary restriction or a milk allergy. If any of these requirements were not met, respondents were asked to return the submission on Prolific, so an available spot would be reopened. After the pilot, some minor technical improvements were implemented before the final survey was released. The same screening questions from the pilot were applied. We compensated each participant $1.25 for a completed response, and we expected the survey to take 6 minutes to complete, for an effective compensation rate of $12.50 per hour. Similar to the pilot, the actual average response time was about five minutes. The final survey was released through Prolific on March 29, 2022, and an additional 700 respondents completed it. The combined 750 responses were pared down to 725 usable responses after removing duplicate participants and an additional screening of participants who did not have anyone in the household who consumed milk. Table 5.1 summarizes the demographic characteristics of the respondents.

Table 5.1. Demographic characteristics of the study sample in relation to the US population.

Variable	Survey respondents (n=725)[1]	U.S. Census data[2]
Age		
19-25[3]	30 (4.1%)	9.1%
26-35	219 (30.2%)	13.8%
36-45	222 (30.6%)	12.8%
46-55	123 (17.0%)	12.6%
56-65	95 (13.1%)	12.9%
65+	36 (5.0%)	15.2%
Gender		
Female	412 (56.9%)	50.5%
Male	300 (41.4%)	49.5%
Non-binary / third gender[4]	9 (1.2%)	-
Prefer to self-describe[4]	3 (0.4%)	-
Ethnicity		
Asian (including South Asian)	47 (6.5%)	5.9%
Black or African American	33 (4.6%)	13.4%
Hispanic/Latino	14 (1.9%)	18.5%
Native Hawaiian or Pacific Islander	1 (0.1%)	0.2%
Two Or More	53 (7.3%)	2.8%
White	575 (79.5%)	76.3%
Highest degree achieved		
Associate degree in college (2-year)	54 (7.5%)	10.50%
Bachelor's degree in college (4-year)	308 (42.5%)	23.50%
Did not complete high school	10 (1.4%)	8.90%
Graduate Degree	135 (18.6%)	14.40%
High school diploma/ GED	95 (13.1%)	27.90%
Some college but no degree	122 (16.9%)	14.90%
Employment status[4]		

A homemaker or stay-at-home parents[5]	61 (8.4%)	-
Other[5]	28 (3.9%)	-
Retired[5]	40 (5.5%)	-
Unemployed and looking for work	55 (7.6%)	5.3%
Working full-time	416 (57.6%)	78.9%
Working part-time	122 (16.9%)	15.8%
Household income		
Less than $10,000	30 (4.2%)	5.5%
$10,000 to $19,999	42 (5.9%)	8.3%
$20,000 to $29,999	65 (9.1%)	8.3%
$30,000 to $39,999	69 (9.6%)	8.2%
$40,000 to $49,999	60 (8.4%)	7.5%
$50,000 to $59,999	69 (9.6%)	7.2%
$60,000 to $69,999	62 (8.6%)	6.2%
$70,000 to $79,999	52 (7.3%)	5.9%
$80,000 to $89,999	39 (5.4%)	4.9%
$90,000 to $99,999	42 (5.9%)	4.4%
$100,000 to $149,999	113 (15.8%)	15.3%
$150,000 or more	74 (10.3%)	18.2%
Marital status		
Divorced	54 (7.6%)	10.82%
Living with a partner	90 (12.6%)	
Married	343 (48.1%)	48.11%
Never married	218 (30.6%)	33.49%
Separated	8 (1.1%)	1.85%
Children under 18		
No	475 (65.7%)	69.30%
Yes	248 (34.3%)	30.70%
Region		
Northeast	147 (20.3%)	17.40%
Midwest	165 (22.8%)	20.80%
South	270 (37.2%)	23.70%
West	143 (19.7%)	38.10%

[1]n(%)
[2]U.S. Census Bureau (2020)
[3]Survey respondents had to be older than 18 years and could not be students. The relative proportion of survey respondents in U.S. Census data will not add to 100% because the population <19 years old were excluded.
[4]U.S. Bureau of Labor Statistics (2021)
[5]U.S. Census or Bureau of Labor Statistics did not report this category

Regressions/models

We analyze the survey data using a series of discrete choice and censored regression models. We estimated several logit models to characterize predictors of poor experience with milk, predictors of switching stores after a poor experience with milk, and predictors of greater likelihood of repurchasing milk. We also estimated a tobit model to examine the factors associated with greater customer loyalty as measured by reported NPS associated with good and poor milk experiences in different market channels.

To determine the predictors of poor experience with milk, the dataset was segmented into three samples: (i) in-store shoppers (n=666), (ii) online shoppers (n=322) and (iii) in-store and online shoppers (n=725) combined. For predictors of poor experience, we constructed a binary variable to indicate whether respondents reported ever having had a poor experience with milk. The explanatory variables represent characteristics related to the respondent and to their purchase behavior, and characteristics of milk type purchased. For predictors of repurchasing milk, we used the top 2 box (T2B) score method to construct the binary variables to indicate the likelihood of returning to the same store or channel to purchase milk. Since NPS is bounded below and above by 0 and 10, we used a tobit model to determine which factors drive this measure. To conduct this analysis, we constructed a panel dataset with 1,442 observations, in which each record reflected a participant's response for a particular type of experience (i.e., good or poor) in a particular market channel (i.e., in-store, store specific website, Instacart, online service).

The explanatory variables evaluated for predictors of switching stores after a poor experience with milk and for predictors of greater likelihood of repurchasing milk included demographic information related to the respondent, purchase milk location (i.e., in-store or online), purchase milk volume (e.g. half-gallon, quart), milk consumption frequency, noticing the sell-by date, milk type (e.g. skim milk, lactose-free milk), and poor experience frequency. The explanatory variables evaluated for the tobit model include these same variables as well as purchase channel (e.g., Instacart, store-specific website).

RESULTS

Summary Statistics

There are some differences when comparing the sample demographic characteristics to the 2020 U.S. Census data (Table 5.1). For instance, 34.3% of the sample are 35 years or younger compared to 46.7% in the Census. In addition, most of the U.S. population are high school graduates, whereas most people in our sample have obtained a bachelor's degree in college. These differences between the sample demographics and the U.S. Census are important factors to consider when generalizing the results to the greater U.S. market.

Consumer purchase behavior pertaining to fluid milk purchases in-store and through eCommerce (i.e., Instacart)

In the survey, we collected data to characterize consumers' milk purchasing behavior (Table 5.2). We find that most people buy groceries of any kind online at least once a month. For milk in particular, about half the participants (55.45%) purchase milk solely in-store and 36.41% purchase it both in-store and online. Individuals in our survey who purchase milk in-store shop for milk primarily at large/national big-box stores (e.g., Walmart, Target, K-Mart) and large supermarkets (e.g., Harps, Tops, Kroger). Individuals who purchase milk online shop for milk primarily through store-specific online services and Instacart. Most respondents who purchase milk in-store purchase milk approximately once a week, whereas 45.03% of respondents who purchase milk online purchase milk less frequently than every 14 days. In addition, 47.72% of respondents usually purchase a gallon of milk, followed by 38.21% who purchase a half-gallon of milk. Most of the respondents buy whole milk and/or 2% milk and notice the sell by date. A large portion of the respondents do not typically buy lactose-free milk, A2 milk, or cream-line milk (Table 5.2).

Table 5.2. Consumer behavioral characteristic pertaining to fluid milk purchases.

Variable	Count (Percentage)
Dietary restrictions (n=725)	
Egg allergy	3 (0.41%)
Fish allergy	2 (0.28%)
Gluten-free	7 (0.97%)
None	612 (84.41%)
Nut allergy	5 (0.69%)
Other dietary restriction	17 (2.34%)
Other food allergies	5 (0.69%)
Shellfish allergy	8 (1.10%)
Soy allergy	3 (0.41%)
Sugar-free	8 (1.10%)
Two or more dietary restrictions	25 (3.45%)
Vegetarian	28 (3.86%)
Wheat or grain allergy	2 (0.28%)
Groceries online purchase frequency (n=725)	
About once a month	162 (22.34%)
About once per week	201 (27.72%)
More than once a week	30 (4.14%)
Once in a few months or longer	189 (26.07%)
Several times a month	143 (19.72%)
Milk purchase channel (n=725)[1]	
In a store	402 (55.45%)
Online (through an app or web browser)	58 (8.00%)
Both in store and online	264 (36.41%)
Milk in-store purchase frequency (n=666) [1]	
Approximately every 10 - 14 days	227 (34.08%)
Approximately once a week	264 (39.64%)
Less frequently than every 14 days	140 (21.02%)
Multiple times a week	33 (4.95%)
Milk in-store purchase location (n=666)	
Warehouse club stores (Costco, Sam's Club, BJ's, etc.)	150 (22.52%)
Large/national big-box stores (Walmart, Target, K-Mart, etc.)	390 (58.56%)

Large supermarkets (Harps, Tops, Sprouts, Kroger, Publix, Albertsons, etc.)	471 (70.72%)
Specialty stores (Whole Foods, Trader Joe's, ethnic grocery stores, etc)	152 (22.82%)
Discount chains (Aldi, Dollar Tree, Dollar General, Big Lots, etc.)	146 (21.92%)
Convenience stores	80 (12.01%)
Small/local grocery stores	151 (22.67%)
Other (please specify)	11 (1.65%)
Milk online purchase frequency (n=322)	
Approximately every 10 - 14 days	96 (29.81%)
Approximately once a week	77 (23.91%)
Less frequently than every 14 days	145 (45.03%)
Multiple times a week	4 (1.24%)
Milk online purchase location (n=322)	
Amazon Fresh	41 (12.73%)
FreshDirect	5 (1.55%)
Instacart	73 (22.67%)
Other (please specify)	21 (6.52%)
PeaPod	4 (1.24%)
Prefer not to answer	2 (0.62%)
Shipt	5 (1.55%)
Store-specific online services (Stop and Shop online delivery/pickup, Walmart+, etc)	171 (53.11%)
Milk consumption frequency (n=725)	
Less than once a week	134 (18.48%)
Multiple times a day	85 (11.72%)
Multiple times a week	283 (39.03%)
Once a day	150 (20.69%)
Once a week	73 (10.07%)
Milk purchase volume size (n=725) [1]	
Gallon	346 (47.72%)
Half-gallon	277 (38.21%)
More than one gallon	19 (2.62%)
Quart	78 (10.76%)
Milk types (n=725) [1]	
Whole milk	343 (47.31%)
2% milk	344 (47.45%)
1% milk	138 (19.03%)
Skim milk	92 (12.69%)
Lactose-free milk	42 (5.79%)
A2 milk	11 (1.52%)
Cream-line milk	14 (1.93%)
Traditional homogenized milk	18 (2.48%)

Milk purchase price (n=725)	
$0-2	61 (8.41%)
$2-4	500 (68.97%)
$4+	164 (22.62%)
Grocery total spend (n=725)[1]	
$100-150	200 (27.59%)
$150+	137 (18.90%)
$25-50	119 (16.41%)
$50-100	252 (34.76%)
Less than $25	15 (2.07%)
Notice sell by date (n=725) [1]	
No	39 (5.38%)
Yes	685 (94.48%)
Poor milk experience (n=725)[1]	
No	364 (50.21%)
Yes	355 (48.97%)
Poor milk experience in-store frequency (n=355)[1]	
About half the time	3 (0.85%)
Always	3 (0.85%)
Most of the time	3 (0.85%)
Never	9 (2.54%)
Rarely	266 (74.93%)
Sometimes	70 (19.72%)
What happened after poor milk experience (n=355)	
Switch stores or providers	50 (14.08%)
Switch milk brand	79 (22.25%)
Switch milk type	12 (3.38%)
Nothing happened	231 (65.07%)

[1]Some participants selected “Prefer not to answer” or “Other”

Consumer insights into poor experiences associated with fluid milk purchases

About half the respondents (49%) have had a poor experience with milk. Figure 5.1 shows what these respondents perceived as a poor milk experience. Respondents were able to select all statements that they considered to be a poor milk experience. Most respondents agree that a poor experience is associated with sensory aspects, with 68.2% of respondents selecting the statement “milk has a sour taste,” 59.2% of respondents selecting “milk not sour but tastes different,” and 55.2% of respondents selecting “milk smells different than expected.” Some respondents also associated a poor milk experience with the expiration date, with 43.7% of respondents selecting “milk reaches expiration date” and 29.9% selecting “milk has two days from expiration.”

Of those consumers who have had a poor milk experience, 65.07% of consumers said nothing would happen while 22.25% said they would switch stores or service providers after a poor experience (Table 5.2).

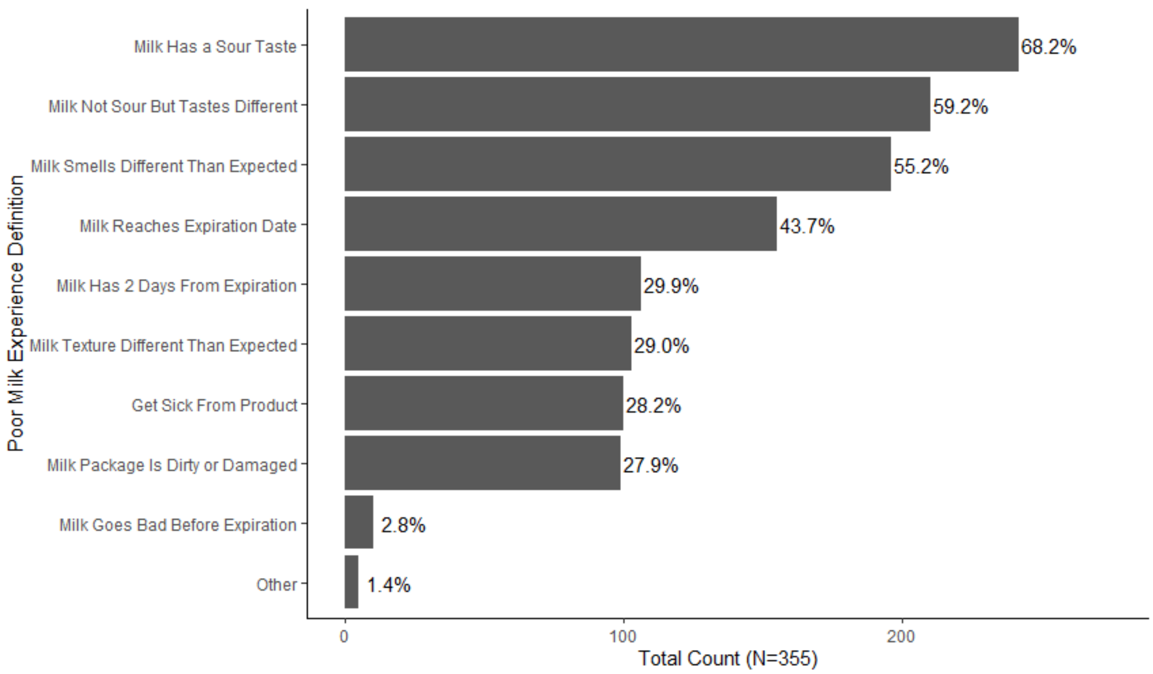

Figure 5.1. Consumers’ perceptions of poor experiences associated with fluid milk purchases. A total count of n=355 represents all survey respondents that reported a poor experience with fluid milk.

Predictors of poor experiences with fluid milk purchased in-store and through eCommerce (i.e., Instacart)

The logit model estimation outcomes for predictors of poor experience are presented in Table 5.3. Model 1, which was estimated with the in-store consumer dataset, had three statistically significant predictors of poor experience: (i) purchase volume of a quart, (ii) purchase volume of more than one gallon and (iii) respondents who notice the sell by date. Similarly, Model 2, which was estimated with the online consumer dataset, had two of the same statistically significant predictors: purchase volume of a quart and purchase volume of more than one gallon. Model 3, which used the combined dataset, had the same three statistically significant predictors of Model 1, as well as a fourth one: purchasing lactose free milk. Based on the Model 3 results, purchasing milk volume of one quart has a logs odd of 0.748 or an odds ratio of 2.1. The reference level for milk purchase volume is one gallon and, thus, the odds of people who purchase a quart of milk having a poor experience are 2.1 times greater than the odds of people who purchase a gallon of milk. Purchasing milk volume greater than one gallon has a logs odd of -1.157 or an odds ratio of 0.31, meaning the odds of people who do not buy more than one gallon having a poor experience are 3.2 times greater than the odds of people who buy one gallon. The odds of people that notice the sell by date having a poor experience are 2.3 times greater than the odds of people who do not notice the sell by date. The odds of people who purchase a lactose free milk having a poor experience are 2.2 times greater than the odds of people who do not purchase a lactose free milk.

Table 5.3. Predictors of poor experience in fluid milk purchased in-store and online

	Model 1 (In-store Dataset)[1]	Model 2 (Online dataset) [1]	Model 3 (Full Dataset) [1]
Milk type_Lactose free	0.692 (0.354).	0.821 (0.628)	0.806 (0.346)*
Milk Purchase Volume_Quart	0.700 (0.306)*	1.254 (0.612)*	0.748 (0.288)**
Milk Purchase Volume_More than a Gallon	-1.302 (0.605)*	-2.519 (1.149)*	-1.157 (0.551)*
Notice sell by date	0.910 (0.407)*	0.710 (0.463)	0.846 (0.3622)*
Log Likelihood	-439.43	-199.65	-481.79
Deviance	878.86	399.29	963.58
AIC	940.86	459.29	1011.58
BIC	1080.4	572.53	1121.65
N	666	322	725

Notes: .p<0.1, *p<0.05, **p<0.01, ***p<0.001
[1]Estimate (Std. Err.)

Predictors of switching stores after a poor experience with fluid milk purchased from in-store and eCommerce (i.e., Instacart)

Our study identified two significant predictors for switching stores after a poor experience with fluid milk: (i) milk purchase volume of a quart and (ii) poor experience frequency. Purchasing a quart volume milk has a negative coefficient, decreasing the odds of switching stores. The odds of people who purchase quart-sized milk switching stores after having a poor experience are 8.4 times less than the odds of people who purchase one gallon of milk. Conversely, poor experience frequency has a positive coefficient, with having a moderate to high poor experience frequency with milk increasing the odds of switching stores by a factor of 2.8.

Predictors of likelihood of repurchasing fluid milk purchased from in-store and eCommerce (i.e., Instacart)

There are two statistically significant predictors of repurchasing fluid milk: (i) milk purchase volume of a half-gallon and (ii) purchasing milk from Instacart (Table 5.4). A purchase volume of half gallon increases the odds of repurchase by a factor of 1.44. The odds of people who purchase fluid milk from Instacart repurchasing milk are 9.2 times greater than the odds of people who purchase fluid milk in-store.

Table 5.4. Regression estimates for switching stores after a poor experience, likelihood of repurchase milk, and net promoter score

	Dependent Variable		
	Switching stores after poor experience[1]	**Likelihood repurchasing milk**[1]	**Net Promoter Score**
Purchased milk volume: Quart	-2.133 (1.079)*		-0.968 (0.295)**
Purchased milk volume: Half-gallon		0.365 (0.159)*	
Poor experience frequency	1.026 (0.374)**		
Instacart channel		2.220 (0.228)***	
Consume milk less than or equal weekly			-0.566 (0.198)**
Purchase milk greater than or equal weekly			0.427 (0.179)*
Notice Sell by date			0.832 (0.361)*
Poor experience			-4.664 (0.169)***
Log Likelihood	-123.95	-675.74	-3107.23
Deviance	247.89	1351.47	
AIC	297.89	1405.47	6270.46
BIC	394.70	1547.86	6418.11
N	355	1442	1441

Note: .p<0.1, *p<0.05, **p<0.01, ***p<0.001. Each column represents a separate regression. The first two columns are logit models; the third column is a tobit model.

[1]Estimate (Std. Err.)

Fluid milk purchase related drivers of NPS for retail stores and eCommerce

There are five statistically significant factors associated with NPS value: (i) milk purchase volume of a quart, (ii) milk consumption once a week or less, (iii) a milk purchase frequency of weekly or multiple times a week, (iv) noticing the sell-by date and (v) having a poor experience (Table 5.4). Respondents who consume milk once a week or less report an NPS value on average 0.566 points less than those who consumes milk once a week. Respondents who purchase quart-sized milk report an NPS value on average 0.968 points less than those who purchase one gallon of milk. Those who notice the sell by date report an NPS value on average 0.832 points higher than those who do not notice the sell by date. Respondents with a poor experience report an NPS value on average 4.664 points lower than those with a good experience. Lastly, respondents who purchase milk once a week or more report an NPS value on average 0.427 points greater than those who purchases milk less frequently than every 14 days.

DISCUSSION

This study examined the effect of a poor experience with fluid milk on grocery purchasing behavior using a survey-based approach. Our results indicate that (i) consumer purchase behavior or product specific sensory attributes (e.g., lactose free milk) are associated with a significantly increased likelihood of poor experience with fluid milk quality; (ii) moderate to high frequencies of poor experiences with milk quality are associated with increased likelihood of switching retail stores; (iii) certain eCommerce channels as well as consumer preferences related to packaging size are associated with an increased likelihood of re-purchasing; and (iv) poor experiences with milk quality negatively impact the NPS, which suggests that having high quality milk can help retailers in their efforts to retain customers.

Predictors of increased likelihood of poor experience with fluid milk quality are

linked to consumer purchase behavior and product specific sensory attributes

We found that two variables, (i) a purchase volume of a quart and (ii) a purchase volume of more than one gallon were significant predictors of having had a poor experience with milk quality across the three subsamples, in-store shoppers (Model 1), online shoppers, (Model 2) and in-store and online shoppers combined (Model 3). The estimated coefficient for a purchase volume of more than one gallon is negative, indicating a decreased likelihood of having a poor experience. One possible explanation is that large volume milk customers may simply consume milk more quickly, before the end of shelf life. Conversely, the estimate coefficient for a purchase volume of a quart was positive, indicating an increased the likelihood of having a poor experience. In this case, because a quart size is a smaller volume, consumers who purchase this volume may be infrequent users or will use it specific occasions, increasing the likelihood of the milk to spoil before its completion. Noticing the sell by date was a significant predictor in Model 1 and Model 3. A possible reason why noticing a sell by date was not statistically significant predictor in Model 2 is because online shoppers are generally unable to view or choose their preferred sell by date in this purchase setting. This choice is left to the sales associate assigned to their order and is therefore no longer a factor for the customer.

Purchasing lactose free milk was only a statistically significant predictor of poor experience in Model 3. Lactose free milk has been associated with higher sweetness and lower viscosity compared to traditional milk flavors, which may not be favorable to some consumers (Adhikari et al., 2010). Some consumers may resort to purchasing lactose-free milk due to their personal intolerances or a household member may require this specific type of milk (Rizzo et al., 2020). Rizzo et al. (2020) found that consumers would prefer that lactose free milk had the same sweetness and texture as traditional milk, which can possibly explain why lactose free milk was found to be a predictor of poor experience in this study. Additionally, lactose free milk is processed at a higher temperature compared to traditional high temperature short time (HTST) milk and thus can have an eggy and cooked flavor profile, which contributes to consumer aversion (Jo et al., 2018, Rizzo et al., 2020). This observation also aligns with the findings in our study. When participants were asked what they perceived as a poor experience, most participants associate a poor experience with dairy milk with a negative sensory experience (Figure 5.1). The top three definitions consumers selected in the survey was associated with the taste and smell of milk. This further emphasizes that product specific sensory attributes can determine whether a consumer has a poor experience with fluid milk.

Having a moderate to high poor experience frequency with fluid milk is associated with a higher likelihood of switching stores

Although a milk purchase volume of a quart was shown to be a significant predictor of poor experience, it did not increase the odds of switching stores after having a poor experience. A milk purchase volume of a quart was one of two significant predictors of switching stores, but because the estimated coefficient was negative, the odds of switching stores decreases with this milk purchase volume. Because a quart size of milk is smaller than other offerings typically found in a retail store, a consumer who had a poor experience with a quart size package size may not be compelled to switch stores. Additionally, consumers who purchase milk of a quart size may be infrequent consumers of milk, in which case this purchase would comprise a small portion of their overall basket size and would not drive switching behavior. This is supported by Rhee and Bell (2002), who determined that most consumers are relatively immobile or unwilling to change their primary stores. However, we observed that having a moderate to high poor experience frequency does in fact increase the odds of a consumer switching stores. This is especially important with online grocery purchases, as one key attribute for online shoppers is product quality (Singh, 2019). Because customers expect to receive the same quality of product they would get if they were at the store themselves, dissatisfaction with the service can result in switching stores (Singh, 2019). Dissatisfaction with the service includes receiving food that is close to the expiration date, which aligns with our findings, where a large portion of consumers associated product nearing its expiration date with a poor experience (Singh, 2019). This reinforces the importance of reducing poor experience with fluid milk to minimize the risk of customers switching stores.

Purchasing through Instacart is associated with greater likelihood of repurchasing milk

Two significant predictors of repurchasing fluid milk are a milk purchase volume of a half gallon and purchasing milk from Instacart. The significance of the milk purchase volume of a half gallon is supported by existing consumer preference studies. McCarthy et. al (2017) conducted a conjoint analysis and found that consumers preferred gallon or half-gallon packaging. Interestingly, Instacart was the only purchasing channel that was a significant predictor of repurchasing fluid milk. This may be a result of the Instacart interface that allows consumers to set up recurring auto-orders and does not require additional effort unlike other online or in-store purchasing channel options. Chintala et al. (2021) previously analyzed the impact of the online grocery retail channel and found that consumers' shopping baskets are heavily influenced by using the past purchases shortcut on the grocery delivery apps. Because online grocery shopping is goal-oriented, shoppers will go elsewhere if the grocer's website or platform is difficult to navigate (Singh, 2019). This presents an opportunity for retailers to either (i) make their store website and/or store app easier to navigate and/or (ii) partner with platforms that are easy to navigate such as Instacart so there is increased likelihood of customers repurchasing from their store.

Having a poor experience with fluid milk will negatively affect NPS

NPS is one of many indicators used to gauge customer loyalty at a store; NPS is measured on a scale from 0 to 10 and is used as an indicator of customer loyalty. A score of 6 or less designates a "detractor;" a score of greater than 6 but less than or equal to 8 designates a "passive," while a score greater than 8 indicates a "promoter." In our study, we measure NPS for the store where a hypothetical purchase was made depending on the consumer's experience with the fluid milk purchased. We found that consumers who have a milk purchase volume of a quart report lower NPS values for the store than those who purchases a gallon of milk. This aligns with our findings when evaluating predictors of a poor experience, where a consumer who purchased a milk volume of a quart had a higher likelihood of having a poor experience. Conversely, noticing the sell by date was associated with higher NPS values, which may be the result of greater awareness of product labels among these respondents which leads to purchasing fluid milk with sell by dates better suited to their needs. Having had a poor experience with fluid milk was associated with an average of NPS value of 4.6 points less than having had a good experience. This has important marketing implications: It suggests that having a negative experience with milk moves a customer from a promoter to a detractor of the retail store based on the NPS scale. Detractors have a negative impact on potential customers, as previous studies have shown that they have the lowest repurchasing rate and account for most negative word-of-mouth comments (Reichheld, 2003, Chang and Fan, 2013). This is especially important as word of mouth has been reported to be a large part of loyalty and to significantly affect consumer purchase decisions (Ha and Im, 2012). Lower NPS values have also been reported to be associated with reduced consumer willingness to pay and thus reduced profits for a firm (Jeanjean, 2011). Consequently, our results suggest that a poor experience with fluid milk in a retail store is likely to translate into reduced promotion of a store (through word of mouth) as well as to reduced visits and/or basket sizes at a store.

CONCLUSION

Our study examines the role that poor experiences with milk products play in retail store choice, repurchase intentions, and customer loyalty in brick-and-mortar and eCommerce retail settings. Ultimately, preventing poor experiences with perishable product by improving and investing in food quality at retail stores can improve customer loyalty and decrease the likelihood of consumers switching retail stores.

Although our study suggests that retail stores may gain substantial economic advantages from ensuring that the fluid milk offerings are of high quality, this study has several limitations that provide opportunities for future research. First, we used an online survey with hypothetical scenarios to understand consumer perceptions and purchasing behaviors in different market channels rather than actual consumer transaction data. Respondents may behave differently when real money is exchanged, and our results may not capture all the nuances of an actual retail setting. Another limitation is that due to the small sample size of respondents that switched stores/service provider after a poor experience, we were unable to draw conclusions on how having a poor experience with a product can affect total grocery spend. Future studies are needed to precisely quantify the impact of negative experiences with fluid milk on the frequency of store visits and basket sizes.

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CHAPTER 6

CONCLUSIONS

Food waste provides a unique challenge along the supply chain because there is not one single solution that can address this issue. While there have been many proposed solutions for diversion and redistribution of food waste, there needs to be a greater emphasis of preventing the generation at the source. Because the greatest portion of food waste occurs at the later stages of the supply chain (e.g. processing plant, retailer and consumer), we focused on providing solutions and courses of action at those stages, as it can have the greatest economic and environmental impact.

In this thesis, we provide the framework for developing decision-support tools that help prevent and reduce food waste. We developed a Monte Carlo model to predict fluid milk spoilage and shelf life, which can be adapted to other food groups by changing several inputs (e.g. storage temperature, initial microbial population). The economic cost can be a barrier for implementing food waste reduction solutions and we addressed this by determining the value of each additional day of shelf life. We then explored a novel approach to displaying shelf life information in a retail setting and how this can help in reducing consumer waste behavior. This is especially important as retailers are finding additional ways to display information and reduce product waste. Retailers such as Walgreens and Kroger have started swapping out fridge and freezer doors with opaque screens that display product information. Digital screens provide opportunities for retailers to implement dynamic pricing and for consumers to access product information. Lastly, the consumer survey we conducted further confirmed the importance of having a high-quality product in stores. Overall, there is a need for increased technology and tools to address food waste and this is an exciting time as we start to see increased implementation to address this in industry.