Sensory optimization of Peruvian Lucuma fruit ice cream using I-Optimal Mixture Design

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Abstract

Consumers are increasingly interested in healthier, more diverse, and culturally inspired ice cream options. Lucuma, a subtropical fruit from the Andes, is gaining popularity in desserts like ice cream due to its natural sweetness and flavor-enhancing properties. Previous research shows that higher levels of Lucuma fruit powder in ice cream affected consumer acceptance. Understanding consumer behavior is crucial in the food industry, with psychographic segmentation providing insights into values and preferences. The objectives of this study were 1) to use i-optimal mixture design for formulating various ice creams with different levels of fat, sugar, and lucuma fruit powder. It also involves evaluating the sensory properties and consumer liking of the prototypes, 2) Optimize consumer liking scores to develop a predictive model that determines maximum ice cream likeability and ideal ingredient levels in the formulation, and 3) To segment consumers based on psychographic data into health-conscious and indulgent groups, to identify sensory response differences in Lucuma ice cream prototypes, and to optimize product formulation for targeted market segments. A total of 11 Lucuma ice creams were produced at the K-State Innovation Kitchen, Olathe. A consumer study (n=104) revealed statistically significant differences in liking between the lucuma ice cream prototypes for all attributes except aroma liking. The flavor profiles varied widely based on product composition, with different levels of lucuma resulting in distinct sensory variations among the prototypes. The study found that optimizing the levels of lucuma fruit powder, sucrose, and milk fat at 1.5%, 13%, and 6.0% respectively led to an overall likeability score of 7.3 among consumers. However, reducing sucrose and increasing lucuma fruit powder resulted in decreased consumer acceptance. Incorporating lucuma fruit powder at optimal levels can enhance the texture of reduced-fat ice cream products. Based on psychographic data, K-means clustering segmented the

consumers into health-conscious (n=53) and indulgent (n=51) groups. The consumer acceptance scores of each segment were used to predict the optimal levels of ingredients for the lucuma ice cream formulations specific to each segment. The overall likeability of the health-conscious group had an optimized score of 7.6 on a 9-point hedonic scale, while the indulgent group scored 7.1 for the same formulation containing 1.5% lucuma fruit powder, 13% sucrose, and 6% fat, indicating a difference in their liking pattern.

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Chapter 1 - Literature Review

Introduction

In recent years, there has been a growing trend among consumers towards healthier food choices (Park, 2018). As a result, the demand for healthier alternatives to traditional desserts, such as fruit-based ice creams and desserts, has been steadily increasing. Consumers are becoming more conscious about their health and are actively seeking out options that can satisfy their cravings for sweets while still fitting into a balanced diet (Sipple et al., 2022). This shift in consumer preferences has created a lucrative market opportunity for the development of healthier ice cream options. By using fruits as the ingredient in ice creams and desserts, manufacturers can tap into this growing demand for healthier options. Incorporating fruits into ice creams and desserts offers numerous benefits. They are rich in fiber, vitamins, minerals, and antioxidants, providing natural sweetness and flavor while reducing the need for excessive sugar, fat and processed additives (Slavin & Lloyd, 2012; Arshad et al., 2022). Fruits also contribute to a refreshing and healthy perception, making them a suitable choice for healthier indulgence (Sütterlin & Siegrist, 2015).

To meet consumer demands for healthier options, manufacturers should develop fruit-based ice creams and desserts that are both delicious and align with health and dietary goals. This approach helps cater to the needs of health-conscious consumers while attracting new ones who may have avoided traditional high-calorie, high-sugar treats (Sipple et al., 2022). Ice cream manufacturers should prioritize research and development to meet evolving consumer demands by focusing on fruit-based ice creams and desserts, offering healthier options to capitalize on market shift.

Ice Cream

Ice cream, with its rich and indulgent history, dates back to ancient civilizations where early forms like flavored snow were enjoyed. The modern version, however, emerged in 16th-century Europe, garnering royal admiration before proliferating globally (Hartel et al., 2017). While initially a luxurious treat for the elite, technological advancements in refrigeration democratized its availability, retaining its cultural status. Today, ice cream symbolizes celebration and comfort worldwide, transcending cultural boundaries and signifying innovation within the dairy industry (Hartel et al., 2017). Its evolution reflects socioeconomic changes and epitomizes culinary globalization (Quinzio, 2009).

Ice cream, as regulated in the United States, is a frozen food product comprised of a combination of water, air, milk fat, nonfat milk solids, flavors, sweeteners, stabilizers, and emulsifiers. The production process is governed by federal guidelines and involves freezing a pasteurized mix while stirring to incorporate air and inhibit ice crystal formation, resulting in its characteristic texture (Goff, 2018). According to U.S. Federal Regulation 21 Code of Federal Regulations (CFR) 135.110, standard ice cream must contain a minimum of 10% milk fat and 10% nonfat milk solids, alongside a requisite density of not less than 1.6 pounds of total solids per gallon and an overall weight of more than 4.5 pounds per gallon. Further regulations categorize ice creams based on their fat content and caloric reduction. For instance, "reduced fat" ice cream contains at least 25% less total fat compared to reference ice cream, whereas "light" or "lite" ice cream must have at least 50% less total fat or 33% fewer calories. "Low-fat" ice cream is defined as having not more than 3 grams of milk fat per serving, and "non-fat" ice cream contains less than 0.5 grams of total fat per serving. There are other varieties of specialty ice cream categories such as "premium" and "super-premium," which contain higher quality ingredients and lower levels of overrun (amount of air incorporated). These regulations in the ice cream market help consumers make informed choices based on nutritional content and quality preferences. Despite the availability of reduced-fat options, regular ice cream continues to be the preferred choice for most consumers in the United States, reflecting a strong preference for richer taste and texture (Goff and Hartel, 2013).

Innovation in ice cream production has played a pivotal role in transforming dessert from an artisanal specialty to a mass-produced commodity. Advancements in refrigeration technology during the 19th century allowed for widespread ice cream distribution, revolutionizing the dairy industry. The introduction of novel freezing techniques and continuous freezers has significantly increased production efficiency (Goff, 2008). Additionally, the integration of new ingredients and texturizers such as hydrocolloids (gum arabic, guar gum, and carrageenan) in ice creams has diversified product offerings to meet varying consumer preferences and dietary requirements. Such innovations have not only enhanced the sensory and nutritional profiles of ice cream but also propelled market growth (Artisanal Ice Cream Market, 2023).

The ice cream sector in the U.S. is adapting to significant shifts in consumer behavior, with wellness, distinctive flavors, and cultural variety as key influences. As more consumers prioritize health, ice cream producers are introducing choices that are lower in fat and sugar and offer dairy-free options. They are also incorporating health-focused ingredients such as vitamins and probiotics into their products to meet the growing demand for nutritious yet indulgent treats. This move towards healthier alternatives signals a positive future direction for the industry (Ice Cream Market in the United States: Market Snapshot to 2020, 2017).

Artisanal and craft ice cream makers are expected to see growth due to a rising consumer preference for ice creams that are not only high in quality but also offer unique flavor experiences. Cultural immersion through flavor represents an emerging trend in the ice cream industry, where internationally inspired flavors are being used to offer consumers a sensory experience that goes beyond traditional tastes. This trend allows people to explore and connect with various world cultures through the distinct flavors of ice cream (Ice Cream Market in the United States: Market Snapshot to 2020, 2017).

To thrive within this changing environment, ice cream manufacturers must stay aligned with what consumers are looking for, a combination of health-conscious choices, exciting and authentic flavors, and a sense of global culture. Together, these trends suggest an evolving industry that both challenges and leverages traditional ideas of ice cream, setting the stage for its continued growth and creativity. The landscape of ice cream and frozen desserts is pivoting significantly towards the inclusion of emerging alternative ingredients, driven by consumer demand for health-conscious options. Driven by consumer demand, manufacturers are embracing alternative ingredients such as plant-based milk substitutes from almond, coconut, cashew, and soy to appeal to lactose-intolerant and vegan demographics. Natural sweeteners like stevia, monk fruit extract, and agave syrup are becoming mainstream, prized for their low glycemic properties, essential for those managing sugar intake (Ice cream trends: Non-dairy and low-sugar NPD soars, but flavor remains key purchasing factor, 2021).

Integrating wholesome elements such as organic fruits, nuts, herbs, and spices adds to the product's health benefits and enriches its flavor profile. Complementing these are fruit purees and powders, which contribute natural sweetness and additional fiber. The adoption of gluten-free flour and organic ingredients aligns with the industry's move towards clean labels and transparent practices, ensuring products are suitable for a wider audience with varying dietary needs. Nutritional enhancements in these frozen treats, like probiotics and fortified vitamins and minerals, signal a transformation of ice cream from a simple indulgence to a treat with health benefits, aligning with consumer trends that favor a 'better-for-you' approach. This evolution highlights a commitment to both flavor and nutritive value, heralding a new era of guilt-free and palate-pleasing indulgences (Sipple et al., 2022).

Lucuma

Lucuma, scientifically known as Pouteria lucuma which originates from the Sapotaceae family, is a subtropical fruit native to the Andean region of South America and is particularly associated with Peru, Chile, and Ecuador. Referred to as the "Gold of the Incas" (Yahia & Guttierrez-Orozco, 2011). Lucuma has historical significance in pre-Hispanic cultures due to its unique taste and nutritional properties. The fruit's golden-yellow flesh bears a resemblance to gold, which may also metaphorically link it to the Inca sun god Inti, underscoring its cultural and divine importance (Campos et al., 2018).

Lucuma fruit has different varietals with distinct characteristics. The two prominent varieties are 'Seda' and 'Palo'. 'Seda' variety has a higher water content, a juicy and tender texture, and is preferred as a table fruit (Ramberg, 2022). The name 'Seda' in Spanish suggests a silky or soft quality, possibly referring to the texture of its flesh. The ‘Palo' variety contains firmer pulp and is mostly used for culinary applications. The unique natural fruit flavor profile with notes reminiscent of sweet potato, butterscotch, and maple syrup is commonly used in sweet goods applications (Ramberg, 2022). Lucuma fruit is recognized for its potential as a "superfood" in the global market, with studies showcasing its use in enhancing the nutritional profile and flavor (García-Ríos et al., 2020).

Lucuma fruit is processed into frozen pulp and flour for long-term storage and convenient use in culinary applications, preserving its nutritional qualities and extending shelf life (Asmat-Campos et al., 2019). The process of preparing frozen lucuma pulp involves washing, peeling, and removing seeds from the fruit. The flesh is then homogenized for a smooth consistency, heat treated to inactivate enzymes and eliminate contaminants, and finally packaged and frozen to preserve its freshness and properties (Yahia and Guttierrez-Orozco, 2011). Lucuma flour is produced by drying the fruit pulp using methods like freeze-drying and low-temperature tray drying. This process yields a finely milled powder while preserving the nutritional attributes of the fruit. It can be used as a sweetener and natural flavor enhancer in desserts, baked goods, and beverages (Ramberg, 2022).

Lucuma is valued not only for its distinctive flavor but also for its nutritional properties (Table 1.1). The composition of Lucuma fruit primarily varies with the variety and the degree of ripeness, presenting a complex matrix of water, carbohydrates, proteins, lipids, organic acids, vitamins, minerals, and phenolic compounds (García-Ríos et al., 2020). Fuentealba et al., (2016) identified that 100g of Lucuma fruit pulp contains total sugars ranging from 11.9 g DW to 33.4 g DW, depending upon the variety and stage of ripeness. The concentrations of simple sugars such as glucose and fructose increase as the fruit ripens, while sucrose levels initially rise but then drop in the ripest fruits. Commercial Lucuma flours from Peru contain sugar content between 231 mg/g DW and 281mg/g DW, as reported by (Ramberg, 2022).

According to research (Table 1.1) conducted by (García-Ríos et al., 2020) the protein content in Beltran and Seda Lucuma varieties ranges from 4.3 to 5.3 g/100 g DW. The fruit also contains a high amount of dietary fiber compared to other fruits, with levels ranging from 23 to 26 g/100g DW consisting of both soluble (3.4 to 5.3 g/100g DW) and insoluble fibers (19 to 21 g/100g DW). Additionally, the starch content is substantial, varying between 11.2 and 17.2 g/100g DW. The total soluble solids (Brix) of the pulps ranged between 21.1 to 24.3. Ramberg (2022), identified the pH values of reconstituted commercial flours (from a mixture of 40 g powder to 60 g of distilled water) is between 5.24 to 5.48.

Dini (2011), have reported the TPC (Total phenolic content) of Lucuma flour to be about 51.1 ± 14.1 mg GAE/1000 g and flavonoid content around 153.2 ± 3.5 mg CE/100 g (Table 1.1). Research led by (Ramberg, 2022) has revealed that fresh Lucuma pulp contains higher levels of total phenolic content compared to its powdered form (Table 1.1). García-Ríos et al.(2020), noted the phenolic content in fresh Beltrán and Seda variety pulps to be around 2.50±0.11 and 2.38±0.13 mg GAE/g DW, respectively. Furthermore, (Ramberg, 2022) highlighted that commercial Lucuma flours present a total phenolic content ranging from 2.10 to 3.00 mg GAE/g DW. Apart from Lucuma fruit variety, maturation, and cultivation, there are other factors that influence the total phenolic content of a Lucuma fruit like post-harvest processing, method of phenol extraction, and analysis.

Table 1.1 Nutritional information of lucuma fruit / lucuma fruit powder

Composition	**Fuentealba et al., (2016)**	**(Ramberg, 2022)**	**(García-Ríos et al., 2020)**	**(Dini, 2011)**
Moisture (g/100 g)			52.5 - 60.2 (P)	
Lipids (g/100 g DW)			1.2 - 1.4	
Protein (g/100 g DW)			4.3 - 5.3 (P)	
Total Sugars (g/100 g DW)	11.9 - 33.4 (P)	23.1 - 28.1 (CLFP)	29.6 - 40.0	
Dietary Fiber (g/100 g DW)			22.8 - 25.6 (P)	
Soluble Fiber (g/100 g DW)			3.4 -5.3 (P)	
Insoluble Fiber (g/100 g DW)			18.5 - 20.8 (P)	
Starch (g/100 g DW)			11.2 - 17.2 (P)	
Total soluble solids (Brix)			21.1 - 24.3 (P)	
pH		5.24 - 5.5 (reconstituted CLFP)	5.5 - 5.6 (P)	
TPC (Total phenolic content)	0.7 ± 0.07 - 61.6 ± 10.9 (mg GAE/g DW)(P)	2.10 - 3.00 (mg GAE/g DW) (CLFP)	2.38±0.13 - 2.50±0.11 (mg GAE/g DW)(P)	51.1 ± 14.1 (mg GAE/1000 g DW) (CLFP)
Flavonoid content	0.50 ± 0.06 - 0.25 ± 0.06 (mg b-carotene/g DW)(P)			153.2 ± 3.5 (mg CE/100 g) (CLFP)

P: Measured on the fresh pulp; CLFP: Commercial Lucuma Fruit Powder; DW: Dry Weight Basis; GAE: Gallic Acid Equivalent; CE: Carotenoids Equivalent

Sensory Research of Lucuma Fruit Powder

The volatile organic compounds responsible for the aroma of ripe lucuma fruit have been investigated in different studies. Taiti et al., (2017) investigated the volatile organic compounds present in ripe lucuma fruit using Proton-transfer-reaction time-of-flight mass spectrometry to analyze the fruit's aroma profile. Over 50 aromatic compounds were identified, with acetylene, methanol, acetaldehyde, and ethanol being the most abundant. The study also found that lucuma fruit lacked significant levels of hemi, mono, and sesquiterpenes. These compounds are commonly found in other fruits like mangoes, strawberries, and citrus fruits and are known to contribute to their characteristic aromas.

The research by (Inga et al., 2019) focused on identifying and quantifying odor-active volatile compounds in lucuma fruit at different ripening stages using gas chromatography-olfactometry and gas chromatography-mass spectrometry to analyze fruit extracts. They found that 2,3-butanedione, methional, (Z)-3-hexenal, (E)-2-hexenal, (Z)-β-ocimene, and 3-methyl butanoic acid were key aroma compounds, contributing to the sweet, green, and rancid notes of ripe lucuma. Notably, the sensory panelists described the aroma of 2,3-butanedione as "lucuma-like," highlighting its contribution to the fruit's unique flavor profile.

Singh (2022), conducted research on 12 different commercial lucuma fruit powders to understand the volatile compounds responsible for the aroma profiles of the products using Gas Chromatography-Mass Spectrometry (GC-MS) and Gas Chromatography – Olfactometry (GC-O). This research revealed the most common aroma attributes present in the Lucuma fruit powders category.

GC-MS was used to identify and quantify the volatile compounds present in the commercial lucuma fruit powders and then GC-O which uses trained panelists to the instrumental analysis to assess the aroma profile of volatile compounds. This method allows scientists to link the chemical data to human sensory experience, providing insight into how each compound contributes to the overall aroma profile perceived by consumers. The volatile analysis of 12 different commercial Lucuma powders produced 38 aroma compounds that were responsible for the release of 28 different aroma notes. The main aroma attributes in all the samples were buttery, sweet, caramelized, waxy, green, nutty, and cucumber. Other aroma notes such as mushroom, brown sweet, grain, plastic, and burnt were also detected.

It is important to note that the compound 2,3-butanedione was found only in the Terrasoul brand sample, producing a buttery aroma. This aligns with previous research findings and other studies characterizing 2,3-butandione as having sweet, buttery-like profiles (Mayer & Grosch, 2001; Inga et al., 2019).

Lucuma Fruit Powder Application in Ice creams

To understand the sensory profile and acceptability of different Lucuma powders in ice cream application, (Singh, 2022) conducted descriptive analysis and a consumer study on 5 Lucuma ice cream samples. Additionally, caramel ice cream (without Lucuma flour but with caramel flavoring) was included for comparison purposes. Five lucuma ice cream samples were prepared using different lucuma powders (selected from 12), each at a 5% (w/w) level in the ice cream mix. The Lucuma powders were selected based on the variation of aroma compounds analyzed from previous instrumental research.

The descriptive panel developed a sensory lexicon with 31 attributes for modalities including appearance, aroma, flavor, aftertaste, and texture. Descriptive analysis results show that the Lucuma ice cream samples were found to be not statistically significant ($p>0.05$) for most of the attributes except color intensity (appearance), caramelized (aroma), brown sweet (flavor), chalkiness (texture), and grainy (texture) particularly when compared with caramel ice cream. The addition of lucuma fruit powder to ice cream resulted in a chalky and grainy texture.

The consumer study (n=104) results found that Terrasoul brand Lucuma powder received higher overall liking scores in ice cream applications compared to regular caramel ice cream in terms of better aroma and flavor.

It is noteworthy to highlight that compound 2,3-butanedione identified in Terrasoul brand Lucuma powder contributed a buttery aroma that could have helped to enhance the aroma and flavor profile of Lucuma ice cream. Product developers could consider Lucuma fruit powders with higher levels of 2,3-butanedione to increase consumer acceptance.

All Lucuma ice creams were penalized for their powdery mouthfeel, caramel flavor and sweetness to be low. The penalty analysis results indicate the potential to increase the flavor of Lucuma fruit in ice cream. However, incorporating 5%(w/w) Lucuma powder into the base mix has been found to affect specific sensory attributes such as color and texture (resulting in chalkiness and graininess) of the ice cream, which could potentially decrease overall consumer liking of the product.

Therefore, one of the objectives of this study is to identify the optimum level of lucuma fruit powder in the ice cream to achieve the right balance between flavor and texture, while also meeting the preferences of health-conscious consumers by decreasing added sugars and fats to enhance both the sensory appeal and nutritional value of the final lucuma ice cream formulation.

Optimization

This research focuses on developing an ice cream formulation with incorporation of Lucuma fruit powder as a key ingredient which is known for its nutrient density and sweet flavor, to strike a balance between indulgence and nutritional benefits, while maximizing consumer acceptance.

The optimization of reduced sugar and fat in ice cream formulations poses a significant challenge to food scientists, demanding an approach that transcends traditional trial-and-error methods. It necessitates a methodologically rigorous framework capable of scrutinizing the complex interactions between various ingredients and their collective impact on the final product's sensory qualities and nutritional profile (McKenzie and Lee, 2022). The RSM (Response Surface Methodology) emerges as a powerful strategy to navigate this multifaceted optimization process by providing a comprehensive understanding of ingredient interactions and allowing for precise targeting of the optimal combination, striking an ideal balance between reducing sugar and fat content while maintaining the desired sensory attributes (Azari-Anpar et al., 2017).

Central to our application of RSM is the employment of mixture designs, a subgroup of experimental designs that are particularly well-suited to the constraints of food formulations, where the ingredients must always total to a fixed sum, typically 100%. This total mixture constraint is intrinsic to many food products, including ice cream, where the proportions of various components such as milk, cream, sweetener, flavorings, and stabilizers are critical to the end product's characteristics (Squeo et al., 2021). Mixture designs systematically vary the proportions of these ingredients to assess not only the direct influence of each component but also their interactive effects (Galvan et al., 2021).

Understanding the foundation of mixture designs within the RSM framework requires the recognition of several key design types, each with its strengths and domain of applicability. Simplex designs, encompassing both lattice and centroid types, offer a structured approach to explore entire composition spaces, often used in preliminary studies such as screening experiments or initial formulation development. D-optimal designs, on the other hand, are more suitable for situations where there are constraints or limitations on ingredient levels, such as cost or availability (Squeo et al., 2021). For this research, however, our focus is on the application of I-optimal mixture design. This design type prioritizes prediction accuracy and minimizes the variance of predicted responses across the design space. By doing so, I-optimal designs provide a higher level of precision in forecasting the outcomes for untested formulations, a critical feature when developing a product aimed at satisfying a broad spectrum of consumer preferences while adhering to nutritional targets (Ozdemir, 2020).

The complexities of I-optimal mixture design can be effectively managed by utilizing specialized statistical software. In our case, the selection of Statease 360 is crucial due to its comprehensive capabilities in experimental design and optimization. This powerful platform empowers researchers not only to construct and analyze I-optimal designs but also to build predictive models and visualize the complex interplay of factors influencing response variables. By utilizing Statease 360, we can engage in an iterative process where each formulation iteration is guided by a progressively refined predictive model (Squeo et al., 2021). This iterative approach plays a fundamental role in efficiently identifying the best possible combination of ingredients for our Lucuma ice cream.

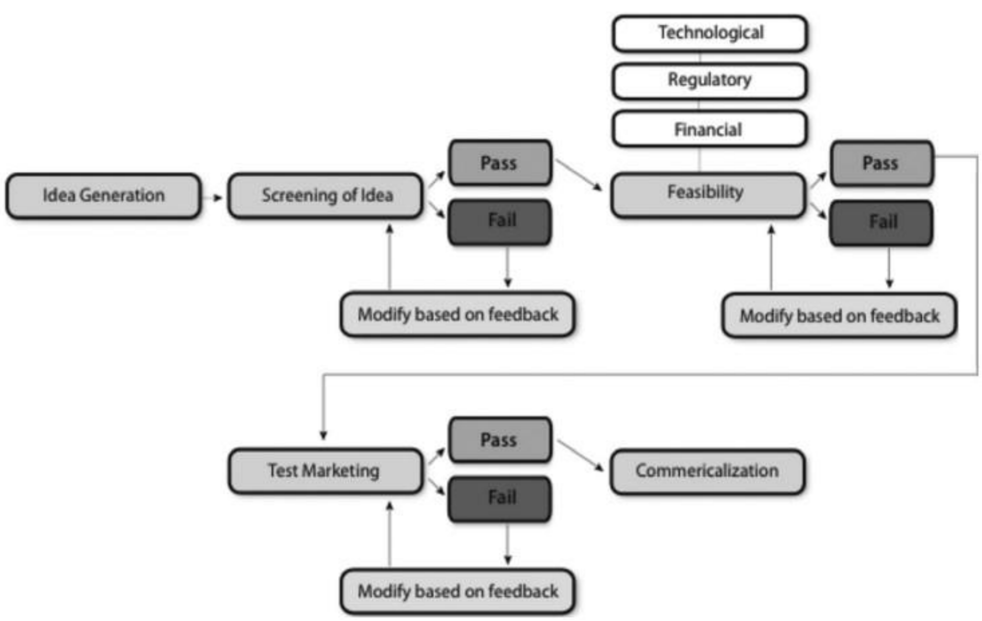
The process of mixture design in the broader context of RSM initiates identifying variables and potential formulations for experimentation. Subsequently, an experimental design was developed to guide the testing of various ingredient combinations. After conducting the experiments, data on consumer responses including appearance, aroma, flavor, texture, and overall liking are collected and analyzed. The information from these experiments enables the development of a predictive model that can accurately forecast outcomes for any combination within the designated space. This predictive model is then utilized to identify an optimal area within the design space where health and taste objectives align effectively - often referred to as the "sweet spot." (Squeo et al., 2021).

In the following sections of our research, we will extensively explore the RSM approach, and the specific mixture design used. This involves a detailed study of the transition from theoretical formulation to practical product development. We plan to analyze the experimental setup using Statease 360, examine the collected empirical data, and obtain valuable insights from the study's results. This study aims to comprehensively analyze the use of an I-optimal mixture design for developing Lucuma ice cream that meets current consumer health preferences while maintaining its desirable sensory characteristics.

Product development and Sensory Analysis

New product development involves a systematic process (Figure 1.1) that involves steps such as idea generation, screening, feasibility studies (regulatory, technology, and financial), test marketing, and commercialization. Assessing the feasibility of a new product idea involves market research, consumer trends, and competitive analysis to ensure demand for the product in the market. Proper validation of the product concept against these metrics increases the chances of success of the product post-launch (Aramouni & Deschenes, 2015). Based on the findings, product developers can create the formulation considering the sensory attributes of the product such as appearance, aroma, flavor, texture, and nutritional content (Ruíz-Capillas & Herrero, 2021; Kumar, R. 2020).

Figure 1.1 The process of product development



Note. Source : Methods for Developing New Food Products, Aramouni & Deschenes, 2015, p.2. Copyright 2015 by DEStech Publications, Inc.

Regulatory feasibility ensures the product meets legal requirements for ingredients, labeling, nutrition, and safety standards. Financial feasibility analyzes the costs of ingredients, production, and distribution to set an appropriate price point balancing profitability with consumer affordability. Technology feasibility evaluates the capabilities and availability of equipment, facilities, and processes needed to manufacture the new product. After product validation and feasibility studies, the development process moves to the prototype creation and testing phase which involves formulating various versions of the new product to identify the ideal combinations of ingredients and processing parameters (Aramouni and Deschenes, 2015). Statistical tools such as the design of experiments are used to design the formulations and process parameters to minimize the experimental runs and to achieve an efficient and cost-effective formulation (Cornell, 2002). The prototype creation and testing phase is crucial for optimizing the product to meet desired sensory attributes, quality standards, and cost-effectiveness (Næs and Nyvold, 2004). After the product is launched, continuous monitoring is necessary to collect consumer feedback, assess product performance, and implement modifications for continuous improvement (Grunert and Trijp, 2014).

Sensory analysis plays a crucial role in various stages of new product development, with a primary focus on evaluating food products based on their sensory attributes. Sensory tests can be categorized into analytical and affective tests. Analytical tests such as discrimination testing and descriptive analysis focus on objectively evaluating product attributes and their intensities by trained panels whereas affective tests are used to measure consumer preferences through methods like acceptance testing using hedonic scales. Selecting the appropriate test method is crucial for obtaining actionable results, with each approach offering different insights (Lawless & Heymann, 2010).

Affective test methods such as acceptance test, preference test, ranking test, paired comparison test, and Check-All-That Apply(CATA) are used to evaluate consumers' emotional responses, preferences, and acceptance of food products qualitatively and quantitatively (Hein et al., 2008). These methods involve untrained panelists who represent typical consumers of the specific product brand, or a similar product category being tested. Acceptance testing assesses consumer preferences and degree of liking towards products based on their sensory characteristics such as appearance, aroma, flavor, texture, aftertaste, and overall liking. Research conducted by (Kwak et al., 2016) on different commercial vanilla ice creams sold in the United States found that negative attributes such as off-aromas (vanillin), bitter taste, off-flavors (metallic), and unsatisfactory mouthfeel/texture (astringency, hardness) significantly affected the consumer acceptance of the overall quality of the ice creams evaluated. Mouthcoating attributes had a positive correlation with consumer liking. The overall liking of a product is a result of the combined effect of individual sensory attributes, their interaction, relative importance, compensatory effects, and consumer variability (Lawless & Heymann, 2010).

By understanding how different sensory attributes contribute to overall liking, product developers can optimize product formulations to enhance consumer satisfaction, improve sensory appeal, and increase the likelihood of product acceptance in the market. Preference tests require consumers to choose their preferred product from a set of options. This method helps identify the most preferred product and can be useful for comparing different formulations or competitor products. More in-depth questions can be asked to understand the reasons behind their preferences and dislikes of the products. Ranking tests help establish the relative preference of products within a set and provide insights into consumer preferences for specific attributes (Lawless & Heymann, 2010). Paired comparison tests require panelists to compare two products at a time and to identify which of two samples has more of an attribute being tested, or to determine which product is preferred (Hein et al., 2008). Check-All-That-Apply (CATA) tests involve consumers selecting all relevant attributes that apply to a product from a list of descriptors. This method helps capture detailed information about consumer perceptions and preferences for specific sensory attributes. Pramudya and Seo, (2018) performed consumer testing on cooked rice which includes CATA questions to understand the sensory attribute variations caused by cooking and serving temperature of the rice samples.

When conducting affective tests in sensory analysis, several crucial factors must be considered to ensure the reliability and validity of the results. These factors include selecting participants who are representative of the target consumer group, preparing samples consistently to maintain uniformity, randomizing sample presentation order to reduce bias, controlling external factors like odor, lighting and temperature for a standardized testing environment, providing clear instructions to participants on evaluation procedures and rating scales, determining an appropriate sample size for statistical significance, using suitable data analysis methods, and adhering to ethical guidelines such as obtaining informed consent and ensuring participant confidentiality. By considering these factors thoughtfully, affective tests can be conducted effectively and obtain robust results. In consumer testing, various types of scales are utilized to gather feedback and evaluate consumer preferences. One common type is the hedonic scale, which measures the degree of liking or disliking of a product on a numerical scale. Another type is the just-about-right (JAR) scale, where participants indicate if a product attribute is too little, just about right, or too much. Likert scales are also frequently used, allowing respondents to express their agreement or disagreement with statements on a scale. Additionally, purchase intent scales assess the likelihood of consumers buying a product. Open-ended questions provide qualitative insights, allowing participants to express their opinions freely. By employing a combination of these scales, researchers can gather comprehensive data on consumer perceptions, preferences, and behaviors in consumer testing scenarios (Lawless & Heymann, 2010).

Statistical tools like ANOVA are used to analyze data in sensory evaluation studies, comparing mean scores of product attributes across multiple products to determine if there are significant differences in liking or acceptance levels. The t-test is commonly used for paired comparisons to evaluate differences in mean scores between two specific groups or conditions, which is instrumental in assessing preferences between two products or treatments. Friedman's test is used for analyzing preference and ranking data, particularly when participants are asked to rank multiple products in order of preference. It helps to determine if there are significant differences in preferences among the products. Penalty analysis is instrumental in scrutinizing Just-About-Right (JAR) data, where consumers express if a product aligns with their expectations, pinpointing areas where products may fall short or exceed consumer expectations, thereby guiding product optimization efforts (Lawless & Heymann, 2010). Other statistical tools such as Response Surface Methodology and mixed models can be implemented in sensory evaluation studies to optimize product ingredients in a formulation and predict the maximum likability level. These tools analyze the relationship between multiple variables (ingredients) in the product formulation and their impact on the liking of sensory attributes.

The Response Surface Methodology is a statistical technique that helps to determine the optimal combination of product ingredients by systematically varying their levels and evaluating sensory responses using hedonic data. Mixed models, on the other hand, consider both fixed effects (such as specific ingredients) and random effects (such as individual consumer liking) to accurately predict the maximum likability level (Cornell, 2002). By utilizing these statistical tools in conjunction with consumer responses, researchers can gain valuable insights into the formulation of products that are not only optimally appealing to consumers but also meet or exceed their expectations in terms of likability.

Attitudinal consumer research focuses on understanding consumers' beliefs, values, preferences, and attitudes towards products or brands. It aims to uncover underlying motivations that drive consumer behavior. In consumer segmentation, attitudinal research helps identify distinct consumer segments based on their attitudes, lifestyles, and psychographic characteristics (Quach and Lee, 2021). By segmenting consumers based on their attitudes, manufacturers can tailor products, messaging, and marketing strategies to better meet the needs and preferences of different consumer groups (Wedowati et al., 2018). This approach allows for more targeted and effective consumer testing by addressing specific attitudes and motivations within each segment. Attitudinal consumer research often utilizes Likert scales, semantic differential scales, and Thurstone scales to measure attitudes, beliefs, and preferences. Likert scales involve respondents indicating their level of agreement or disagreement with statements, while semantic differential scales measure attitudes based on opposite adjectives. Thurstone scales require respondents to rate statements based on their perceived relevance to the topic (Arul and Misra, 1977).

Research conducted by (Saba et al., 2019) utilizes the Health and Taste Attitude Scales to evaluate the importance consumers place on health and taste in food choices. It segments consumers by preferences, aiding in designing effective healthy eating promotional strategies. These scales are used in attitudinal consumer research to quantify and analyze consumer attitudes toward products, brands, or marketing campaigns. By collecting data through these scales, researchers can identify patterns, trends, and differences in attitudes among different consumer segments. This information helps marketers understand consumer preferences, tailor their strategies to specific target audiences, and make informed decisions to enhance product development and marketing efforts.

Research Objectives

The focus on health and wellness has increased the need for clear information about food products. Consumers are looking for "clean label" products with less processed sugars, lower milk fat content, and fewer synthetic additives. This trend emphasizes the need to reconsider traditional ingredients such as sucrose and milk fat and explore alternative formulations that align with consumer preferences for natural, nutritious options while retaining sensory qualities.

Objective 1A. The study aims to use an i-optimal mixture design to create different ice cream formulations by varying the levels of key ingredients: fat, sugar, and Lucuma fruit powder within specific limits while minimizing experimental trials.

Objective 1B. Develop 11 Lucuma ice cream prototypes based on the formulations derived from an i-optimal mixture design to assess consumer acceptance.

Objective 1C. Perform a central location test with frequent ice cream consumers to understand the sensory attributes and consumer liking for 11 different Lucuma ice cream prototypes developed.

Objective 2. Analyze consumer liking scores to develop a predictive model that determines maximum ice cream likeability and optimal ingredient levels in the formulation.

Objective 3. To identify how health-conscious and indulgent consumer segments differ in their sensory evaluation of Lucuma ice cream prototypes and to apply these insights to optimize the product formulation for targeted market segments.

References

Park, Y W. (2018, January 1). Recent Trend in the Dairy Industry. OMICS Publishing Group, 06(04). https://doi.org/https://doi.org/10.4172/2329-888x.1000e134

Sipple, L., Racette, C., Schiano, A., & Drake, M. (2022, January 1). Consumer perception of ice cream and frozen desserts in the “better-for-you” category. Elsevier BV, 105(1), 154-169. https://doi.org/10.3168/jds.2021-21029

Slavin, J L., & Lloyd, B. (2012, July 1). Health Benefits of Fruits and Vegetables. Elsevier BV, 3(4), 506-516. https://doi.org/https://doi.org/10.3945/an.112.002154

Arshad, S., Rehman, T., Saif, S., Rajoka, M S R., Ranjha, M M A N., Hassoun, A., Cropotova, J., Trif, M., Younas, A., & Aadil, R M. (2022, September 1). Replacement of refined sugar by natural sweeteners: focus on potential health benefits. Elsevier BV, 8(9), e10711-e10711. https://doi.org/https://doi.org/10.1016/j.heliyon.2022.e10711

Sütterlin, B., & Siegrist, M. (2015, December 1). Simply adding the word “fruit” makes sugar healthier: The misleading effect of symbolic information on the perceived healthiness of food. Elsevier BV, 95, 252-261. https://doi.org/https://doi.org/10.1016/j.appet.2015.07.011

Hartel, R W., Rankin, S A., & Bradley, R L. (2017, December 1). A 100-Year Review: Milestones in the development of frozen desserts. Journal of dairy science, 100(12), 10014-10025. https://doi.org/10.3168/jds.2017-13278

Quinzio, J. (2009, May 5). Of Sugar and Snow: A History of Ice Cream Making. https://www.google.com/books/edition/Of_Sugar_and_Snow/9OEmdcwYhfEC

Goff, H D. (2018, January 1). Ice Cream and Frozen Desserts: Product Types. https://doi.org/10.1016/b978-0-08-100596-5.00833-7

Goff, H D., & Hartel, R W. (2013, January 1). Ice Cream. Springer eBooks. https://doi.org/10.1007/978-1-4614-6096-1

Goff, H D. (2008, July 1). 65 Years of ice cream science. International dairy journal, 18(7), 754-758. https://doi.org/10.1016/j.idairyj.2008.03.006

Artisanal Ice Cream Market. (2023, January 1). https://www.coherentmarketinsights.com/insight/artisanal-ice-cream-market-2967/toc

Ice Cream Market in the United States: Market Snapshot to 2020. (2017, February 1). https://www.proquest.com/reports/ice-cream-market-united-states-snapshot-2020/docview/1872816196/se-2

Ice cream trends: Non-dairy and low-sugar NPD soars, but flavor remains key purchasing factor. (2021, July 12). https://www.foodingredientsfirst.com/news/ice-cream-trends-non-dairy-and-low-sugar-npd-soars-but-flavor-remains-key-purchasing-factor.html

Sipple, L., Racette, C., Schiano, A., & Drake, M. (2022, January 1). Consumer perception of ice cream and frozen desserts in the “better-for-you” category. Elsevier BV, 105(1), 154-169. https://doi.org/10.3168/jds.2021-21029

Yahia, E M., & Guttierrez-Orozco, F. (2011, January 4). Postharvest biology and technology of tropical and subtropical fruits, Lucuma (Pouteria lucuma (Ruiz and Pav.) Kuntze). Woodhead Publishing Series in Food Science, Technology and Nutrition, 3, 443-449. https://www.sciencedirect.com/science/article/pii/B9781845697358500188

Campos, D., Chirinos, R., Ranilla, L G., & Pedreschi, R. (2018, January 1). Bioactive Potential of Andean Fruits, Seeds, and Tubers. Elsevier BV, 287-343. https://doi.org/https://doi.org/10.1016/bs.afnr.2017.12.005

Yahia, E M., & Guttierrez-Orozco, F. (2011, January 4). Postharvest biology and technology of tropical and subtropical fruits, Lucuma (Pouteria lucuma (Ruiz and Pav.) Kuntze). Woodhead Publishing Series in Food Science, Technology and Nutrition, 3, 443-449. https://www.sciencedirect.com/science/article/pii/B9781845697358500188

Ramberg, E. (2022, January 4). Compositional analysis of the Andean fruit Pouteria Lucuma A comparison of different physical forms (powder, frozen pulp and fresh pulp)

García-Ríos, D., Aguilar-Galvez, A., Chirinos, R., Pedreschi, R., & Campos, D. (2020, April 15). Relevant physicochemical properties and metabolites with functional properties of two commercial varieties of Peruvian Pouteria lucuma. 2020 Wiley Periodicals, 44(6). https://doi.org/https://doi.org/10.1111/jfpp.14479

Asmat-Campos, D., Carreño-Ortega, Á., & Díaz-Pérez, M. (2019, February 21). Recovering-Innovation-Exportation Triangle as an Instrument for Sustainable Development: Proposal for Peruvian Agro-Export Development. Sustainability, 11(4), 1149-1149. https://doi.org/10.3390/su11041149

Yahia, E M., & Guttierrez-Orozco, F. (2011, January 1). Lucuma (Pouteria lucuma (Ruiz and Pav.) Kuntze). Elsevier BV, 443-450e. https://doi.org/https://doi.org/10.1533/9780857092885.443

Ramberg, E. (2022, January 4). Compositional analysis of the Andean fruit Pouteria Lucuma A comparison of different physical forms (powder, frozen pulp and fresh pulp)

García-Ríos, D., Aguilar-Galvez, A., Chirinos, R., Pedreschi, R., & Campos, D. (2020, April 15). Relevant physicochemical properties and metabolites with functional properties of two commercial varieties of Peruvian Pouteria lucuma. 2020 Wiley Periodicals, 44(6). https://doi.org/https://doi.org/10.1111/jfpp.14479

Fuentealba, C., Gálvez, L., Cobos, A., Olaeta, J A., Defilippi, B G., Chirinos, R., Campos, D., & Pedreschi, R. (2016, January 1). Characterization of main primary and secondary metabolites and in vitro antioxidant and antihyperglycemic properties in the mesocarp of three biotypes of Pouteria lucuma. Elsevier BV, 190, 403-411. https://doi.org/https://doi.org/10.1016/j.foodchem.2015.05.111

Dini, I. (2011, February 1). Flavonoid glycosides from Pouteria obovata (R. Br.) fruit flour. Elsevier BV, 124(3), 884-888. https://doi.org/https://doi.org/10.1016/j.foodchem.2010.07.013

Singh, G. (2022, February 8). Sensory and consumer evaluation of lucuma powder as an ingredient for ice cream in the United States

Mayer, F., & Grosch, W. (2001, March 13). Aroma simulation on the basis of the odourant composition of roasted coffee headspace†. Wiley, 16(3), 180-190. https://doi.org/https://doi.org/10.1002/ffj.975

Inga, M., García, J M., Aguilar-Galvez, A., Campos, D., & Osorio, C. (2019, January 1). Chemical characterization of odour-active volatile compounds during lucuma

(<i>Pouteria lucuma</i>) fruit ripening. Taylor & Francis, 17(1), 494-500. https://doi.org/https://doi.org/10.1080/19476337.2019.1593248

Taiti, C., Colzi, I., Azzarello, E., & Mancuso, S. (2017, May 31). Discovering a volatile organic compound fingerprinting of Pouteria lucuma fruits. EDP Sciences, 72(3), 131-138. https://doi.org/10.17660/th2017/72.3.2

McKenzie, E., & Lee, S Y. (2022, March 8). Sugar reduction methods and their application in confections: a review. Food Science and Biotechnology, 31(4), 387-398. https://doi.org/10.1007/s10068-022-01046-7

Azari-Anpar, M., Khomeiri, M., Ghafouri-Oskuei, H., & Aghajani, N. (2017, March 3). Response surface optimization of low-fat ice cream production by using resistant starch and maltodextrin as a fat replacing agent. Journal of Food Science and Technology, 54(5), 1175-1183. https://doi.org/10.1007/s13197-017-2492-0

Squeo, G., Angelis, D D., Leardi, R., Summo, C., & Caponio, F. (2021, May 19). Background, Applications and Issues of the Experimental Designs for Mixture in the Food Sector. Foods, 10(5), 1128-1128. https://doi.org/10.3390/foods10051128

Galvan, D., Effting, L., Cremasco, H., & Conté-Júnior, C A. (2021, August 20). Recent Applications of Mixture Designs in Beverages, Foods, and Pharmaceutical Health: A Systematic Review and Meta-Analysis. Foods, 10(8), 1941-1941. https://doi.org/10.3390/foods10081941

Ozdemir, A. (2020, March 19). An I-optimal experimental design-embedded nonlinear lexicographic goal programming model for optimization of controllable design factors. https://www.tandfonline.com/doi/full/10.1080/0305215X.2020.1732365

ARAMOUNI, F., & DESCHENES, K. (2015, January 6). METHODS for DEVELOPING NEW FOOD PRODUCTS An Instructional Guide. DEStech Publications, Incorporated

Ruíz-Capillas, C., & Herrero, A M. (2021, March 10). Sensory Analysis and Consumer Research in New Product Development. Multidisciplinary Digital Publishing Institute, 10(3), 582-582. https://doi.org/https://doi.org/10.3390/foods10030582

CORNELL, J. (2002, January 24). Experiments with Mixtures. https://onlinelibrary.wiley.com/doi/book/10.1002/9781118204221

Næs, T., & Nyvold, T E. (2004, March 1). Creative design—an efficient tool for product development. Elsevier BV, 15(2), 97-104. https://doi.org/https://doi.org/10.1016/s0950-3293(03)00036-3

Pecore, S., & Kellen, L A. (2002, September 1). A consumer-focused QC/sensory program in the food industry. Elsevier BV, 13(6), 369-374. https://doi.org/https://doi.org/10.1016/s0950-3293(02)00058-7

Civille, G V., & Oftedal, K N. (2012, November 1). Sensory evaluation techniques — Make “good for you” taste “good”. Elsevier BV, 107(4), 598-605. https://doi.org/https://doi.org/10.1016/j.physbeh.2012.04.015

Lawless, H T., & Heymann, H. (2010, January 1). Sensory Evaluation of Food. Food science text series. https://doi.org/10.1007/978-1-4419-6488-5

O’Sullivan, M G. (2020, January 1). Discrimination testing for reformulated products. Elsevier BV, 215-226. https://doi.org/https://doi.org/10.1016/b978-0-12-819741-7.00009-2

Murray, J., Delahunty, C M., & Baxter, I A. (2001, January 1). Descriptive sensory analysis: past, present and future. Food research international, 34(6), 461-471. https://doi.org/10.1016/s0963-9969(01)00070-9

Hein, K A., Jaeger, S R., Carr, B T., & Delahunty, C M. (2008, October 1). Comparison of five common acceptance and preference methods. Elsevier BV, 19(7), 651-661. https://doi.org/https://doi.org/10.1016/j.foodqual.2008.06.001

CORNELL, J. (2002, January 24). Experiments with Mixtures. https://onlinelibrary.wiley.com/doi/book/10.1002/9781118204221

Drake, M., Watson, M E., & Liu, Y. (2023, March 27). Sensory Analysis and Consumer Preference: Best Practices. Annual Reviews, 14(1), 427-448. https://doi.org/https://doi.org/10.1146/annurev-food-060721-023619

Quach, X., & Lee, S H. (2021, March 30). Profiling gifters via a psychographic segmentation analysis: insights for retailers. Emerald Publishing Limited, 49(10), 1391-1410. https://doi.org/https://doi.org/10.1108/ijrdm-10-2020-0420

Wedowati, E R., Singgih, M L., & Gunarta, I K. (2018, January 1). A study of consumer preferences for customized product design. EDP Sciences, 204, 01002-01002. https://doi.org/https://doi.org/10.1051/matecconf/201820401002

Arul, M., & Misra, B. (1977, January 3). The Measurement of Attitudes. Indian Institute of Management Ahmedabad, Research and Publication Department, IIMA Working Papers.. https://www.researchgate.net/publication/46435712_Measurement_of_Attitudes

Saba, A., Sinesio, F., Moneta, E., Dinnella, C., Laureati, M., Torri, L., Peparaio, M., Civitelli, E S., Endrizzi, I., Gasperi, F., Bendini, A., Toschi, T G., Predieri, S., Abbà, S., Bailetti, L., Proserpio, C., & Spinelli, S. (2019, April 1). Measuring consumers attitudes towards health and taste and their association with food-related life-styles and preferences. Elsevier BV, 73, 25-37. https://doi.org/https://doi.org/10.1016/j.foodqual.2018.11.017

Kumar, R. (2020). A strategy for using sensory analysis for category appraisal to develop new and improved products (Order No. 28155888). Available from Dissertations & Theses @ Kansas State University; ProQuest One Academic. (2491976604). Retrieved from https://er.lib.k-state.edu/login?url=https://www.proquest.com/dissertations-theses/strategy-using-sensory-analysis-category/docview/2491976604/se-2

Grunert, K G., & Trijp, H C M V. (2014, November 5). Consumer oriented new product development. https://www.sciencedirect.com/science/article/pii/B9780444525123000620

Squeo, G., Angelis, D D., Leardi, R., Summo, C., & Caponio, F. (2021, May 19). Background, Applications and Issues of the Experimental Designs for Mixture in the Food Sector. Foods, 10(5), 1128-1128. https://doi.org/10.3390/foods10051128

Kwak, H S., Meullenet, J., & Lee, Y. (2016, April 18). Sensory profile, consumer acceptance and driving sensory attributes for commercial vanilla ice creams marketed in the United States. Wiley-Blackwell, 69(3), 346-355. https://doi.org/https://doi.org/10.1111/1471-0307.12314

Hein, K A., Jaeger, S R., Carr, B T., & Delahunty, C M. (2008, October 1). Comparison of five common acceptance and preference methods. Food quality and preference, 19(7), 651-661. https://doi.org/10.1016/j.foodqual.2008.06.001

Pramudya, R C., & Seo, H. (2018, March 1). Using Check-All-That-Apply (CATA) method for determining product temperature-dependent sensory-attribute variations: A case study of cooked rice. Elsevier BV, 105, 724-732. https://doi.org/https://doi.org/10.1016/j.foodres.2017.11.075

Chapter 2 - Development of Lucuma Ice Cream and Testing the Consumer Acceptance

Abstract

This research aims to conduct a technical analysis (added sugar % and fat %) of commercially available ice creams in the United States, design experimental trial runs to produce lucuma ice creams with diverse sensory characteristics by varying the proportion of ingredients, and to develop prototypes to conduct sensory and consumer testing with enough differentiation among products to maximize learnings. The technical analysis of the ice cream category was performed using the market intelligence tool Mintel to understand the nutritional makeup of various ice cream products available in the United States. This information was then utilized to establish limits (% Wt./Wt.) for key ingredients (Lucuma fruit powder, added sugars (sucrose), and milk fat (heavy cream) in the liquid mix of the ice cream formulation. Based on the market analysis and preliminary lab trials, the upper and lower limits for lucuma fruit powder were set in the range of 1.5% to 7% while both milk fat and sucrose range were set between 6% and 13% in the liquid mix of the ice cream formulation to design the experimental trial runs. Using optimal mixture design with Statease 360 software, a total of 11 different Lucuma ice cream trial runs were designed. This experimental approach involves interrelated variables where the proportions are dependent on each other to add up to 100%. Detailed formulations were developed for each of the 11 Lucuma ice cream trial runs, specifying the exact quantities of ingredients to be used in the ice cream production process using Tech Wizzard formulation software. Once the formulations were developed, batch sizes were determined based on the required quantity of ice cream for a consumer study. Ingredients were then procured from various sources including heavy cream, sucrose, non-fat dry milk, soluble corn solids, stabilizers, lucuma fruit powder, and

whole milk. A total of 11 lucuma ice creams were produced at the K-State Innovation kitchen, Olathe using Carpigiani ice cream machines and stored at -7.6°F for the consumer study. A central location consumer test was conducted over two days using a completely balanced randomized design with ice cream consumers (n=104). The consumer test revealed a statistically significant difference ($p<0.05$) in liking between the lucuma ice cream prototypes for all attributes, except aroma liking reaching the desired differentiation among products. Prototypes containing higher lucuma fruit powder received the penalty for being too dark in color. CATA results indicated a wide variation in the flavor profiles of prototypes based on their product composition. Consumers perceived mild flavors such as creamy, vanilla, milky, French vanilla, and buttery in prototypes with low levels of lucuma. Higher lucuma levels resulted in stronger flavor attributes such as nutty, chemical/artificial, bitterness, and overripe fruit. Prototypes with moderate levels of lucuma were associated with attributes related to caramel, butter pecan, butterscotch, and maple syrup, indicating significant sensory variation among the prototypes.

Introduction

Ice cream has a rich history dating back to ancient civilizations, with modern versions emerging in 16th-century Europe. It was initially a luxurious treat for the elite but became more widely available due to technological advancements in refrigeration (Hartel et al., 2017). Today, ice cream symbolizes celebration and comfort worldwide, reflecting socioeconomic changes and culinary globalization (Quinzio, 2009).

Ice cream, as regulated in the United States, is a frozen food product comprised of a combination of water, air, milk fat, nonfat milk solids, flavors, sweeteners, stabilizers, and emulsifiers. The production process is governed by federal guidelines and involves freezing a pasteurized mix while stirring to incorporate air and inhibit ice crystal formation, resulting in its characteristic texture (Goff, 2018). According to U.S. Federal Regulation 21 CFR 135.110, standard ice cream must contain a minimum of 10% milk fat and 10% nonfat milk solids, alongside a density of not less than 1.6 pounds of total solids per gallon and an overall weight of more than 4.5 pounds per gallon. Further regulations categorize ice creams based on their fat content and caloric reduction. For instance, "reduced fat" ice cream contains at least 25% less total fat compared to reference ice cream, whereas "light" or "lite" ice cream must have at least 50% less total fat or 33% fewer calories. "Low-fat" ice cream is defined as having not more than 3 grams of milk fat per serving, and "non-fat" ice cream contains less than 0.5 grams of total fat per serving. There are other varieties of specialty ice cream categories such as "premium" and "super-premium," which contain higher quality ingredients and lower levels of overrun (amount of air incorporated). These regulations in the ice cream market help consumers make informed choices based on nutritional content and quality preferences. Despite the availability of reduced-fat options, regular ice cream continues to be the preferred choice for most consumers in the United States, reflecting a strong preference for richer taste and texture (Goff & Hartel, 2013).

Ice cream production has evolved significantly, from being artisanal to mass-produced, due to innovations in refrigeration technology and freezing techniques (Goff, 2008). The introduction of new ingredients and texturizers has diversified product offerings to meet consumer preferences and dietary requirements, enhancing both the sensory and nutritional profiles of ice cream (Artisanal Ice Cream Market, 2023).

The ice cream industry in the U.S. is changing to align with shifts in consumer behavior, focusing on wellness, unique flavors, and cultural diversity. Producers are introducing healthier options with lower fat and sugar content, clean labels, less processed ingredients as well as dairy-free choices to cater to health-conscious consumers. Furthermore, they are incorporating fruit fibers, polyphenols/antioxidants, vitamins, and probiotics into their products to fulfill the demand for nutritious yet indulgent treats, indicating a positive future direction for the industry (Ice Cream Market in the United States: Market Snapshot to 2020, 2017)

Artisanal and craft ice cream makers are expected to see growth due to a rising consumer preference for high-quality, unique flavor experiences. This trend involves using internationally inspired flavors to offer consumers a sensory experience that goes beyond traditional tastes, allowing them to explore and connect with various world cultures (Ice Cream Market in the United States: Market Snapshot to 2020, 2017).

The landscape of ice cream and frozen desserts is pivoting significantly towards the inclusion of emerging alternative ingredients, driven by consumer demand for health-conscious options. Driven by consumer demand, manufacturers are embracing alternative ingredients such as plant-based milk substitutes from almond, coconut, cashew, and soy to appeal to lactose-intolerant and vegan demographics. Natural sweeteners like stevia, monk fruit extract, and agave syrup are becoming mainstream, prized for their low glycemic properties, essential for those managing sugar intake (Ice cream trends: Non-dairy and low-sugar NPD soars, but flavor remains key purchasing factor, 2021).

Integrating wholesome elements such as organic fruits, nuts, herbs, and spices adds to the product's health benefits and enriches its flavor profile. Complementing these are fruit purees and powders, which contribute natural sweetness and additional fiber. The adoption of gluten-free flour and organic ingredients aligns with the industry's move towards clean labels and transparent practices, ensuring products are suitable for a wider audience with varying dietary needs. Nutritional enhancements in these frozen treats, such as probiotics and fortified vitamins and minerals, signal a transformation of ice cream from a simple indulgence to a treat with health benefits, aligning with consumer trends that favor a 'better-for-you' approach. This evolution highlights a commitment to both flavor and nutritive value, heralding a new era of guilt-free and palate-pleasing indulgences .

The incorporation of organic fruits, nuts, herbs, and spices adds to the product's health benefits and enriches its flavor. Fruit purees and powders contribute natural sweetness and fiber. The use of gluten-free flour and organic ingredients aligns with clean labels and transparent practices in the industry. Nutritional enhancements like prebiotics and probiotics signal a transformation of ice cream from a simple indulgence to a treat with health benefits, in line with consumer trends favoring a 'better-for-you' approach. This evolution highlights commitment to both flavor and nutritive value, heralding an era of guilt-free indulgences (Sipple et al., 2022).

Lucuma fruit, scientifically known as Pouteria lucuma, is native to the Andean region of South America and belongs to the Sapotaceae family (Yahia & Guttierrez-Orozco, 2011). The fruit is processed into powder form for a longer shelf life and has various properties such as being a natural sweetener, fruit fiber source, flavoring agent, gluten-free flour alternative with many culinary applications. Adding lucuma fruit powder to desserts like ice cream provides a unique flavor and aroma while enhancing the nutritional profile through its natural antioxidant and fiber content. It also contributes natural sweetness and improves the mouthfeel of the ice cream.

According to previous sensory consumer research (Singh, 2022), the addition of lucuma fruit powder in ice creams at 5 % (Wt./Wt.) has been found to affect specific sensory attributes such as color and texture (resulting in chalkiness and graininess) of the ice cream, which could potentially decrease overall consumer liking of the product.

Therefore, one of our objectives is to identify the optimum levels of lucuma fruit powder to achieve a balance between flavor and texture, while also meeting the preferences of health-conscious consumers by decreasing added sugars and fats to enhance both the sensory appeal and nutritional value of the final lucuma ice cream formulation. This will be achieved through Design of Experiments (DOE) and a mixture design in a Central Location Test (CLT). However, to get to that, we will first need to develop prototypes that provide a wide range of sensory properties to maximize learnings, which is this chapter's objective.

Optimization in food research involves utilizing statistical principles and structured experimental designs to achieve the best outcomes in product formulations and processes. Statistical tools like Design of Experiments (DOE) and mixture design methodologies play a crucial role in systematically exploring the effects of various ingredients on product development results. DOE allows for the optimization of processes and products by varying input factors to observe their effects on the output response, particularly in understanding how different ingredients and process parameters influence the quality and appeal of the final product. Mixture design, a specialized technique within DOE, is essential for formulating complex products with multiple interacting ingredients to create desired characteristics. The goal of mixture design is to determine the optimal combination of ingredients that will result in the desired response, whether it is to maximize or minimize a specific property. By analyzing the proportions of components in the mixture, researchers can understand how each ingredient contributes to the overall outcome and identify the optimal blend for achieving desired results, especially in exploring the effects of ingredient combinations on sensory attributes in new product development.

Central Location Test (CLT) is a widely used quantitative method that assesses consumer acceptance of products in a controlled environment, conducted by sensory professionals at a specific location. (Kwak et al., 2016) studied the key sensory attributes that drive consumer preferences for commercial vanilla ice creams marketed in the United States. Another study found that variations in fat content impact the consumer acceptance of vanilla ice cream (Rolon et al., 2017).

This study aims to use Design of Experiments and mixture design methodologies, particularly focusing on optimal mixture design, to develop different lucuma ice cream prototypes by varying the proportion of ingredients within the design space planned. Below we proceed to explain the steps to develop prototypes using Design of Experiments and Optimal Mixture Design.

Materials

Software

Mintel market intelligence tool was used to conduct technical analysis and gather data on different ice cream products launched in the United States market. Statease 360 software was used for designing the experimental trial runs and optimizing the ingredients in lucuma Ice cream formulations. Formulation software, Tech Wizard was used to formulate the ice cream batches and calculate the product composition. Microsoft XLSTAT 2000 was used for statistical data analysis. The online screener and questionnaire (Compusense Cloud software, Compusense Inc., Guelph, Canada) were used to screen participants and collect data on acceptance and sensory profiles from the participants.

Ingredients

The ice creams were produced with ingredients from different sources listed in Table 2.1, including whole milk (3.25% fat), heavy cream (36% fat), non-fat dry milk, granulated sugar, soluble corn solids, stabilizer/emulsifier, and lucuma fruit powder.

Equipment

The ice creams were prepared at the K-State Olathe innovation kitchen using the equipment listed in Table 2.2. Figure 2.1 shows the pictures of the pasteurizer, homogenizer, batch freezer, blast freezer, and deep freezer. Other equipment and utensils such as hand blenders, beakers, mixing bowls, whisks, spatulas, and thermometers were used from the K-State Olathe innovation kitchen.

Table 2.1 Ingredients used for manufacturing lucuma ice cream

Ingredients	Product Grade	Source/Brand
Whole Milk	Pasteurised Whole Milk (3.25% fat)	Great Value (Walmart)
Heavy Cream	Pasteurised frozen heavy cream (36% fat)	Hiland heavy cream
Non Fat Dry Milk	Grade A Non Fat Dry Milk	Dairy America
Sucrose	Sugar Granulated Extra Fine Cane	Sysco
Stabilisers/Emulsifiers	Grindsted ICEPRO	Danisco
Soluble Corn solids	Maltrin M200	Grain Processing Corporation
Lucuma Fruit powder	Organic lucuma powder	Terrasoul

Packaging

Half-gallon poly-coated paper cup with a lid was used to package the ice cream samples for storage and transportation purposes.

Table 2.2 Equipment used for manufacturing lucuma ice creams

Equipment	Function
Carpigiani RTX120	Blending, Pasteurization and Aging
Carpigiani Turbo mix	Shear blending/ homogenization
Carpigiani LB300G	Batch freezing
Blast freezer	Blast freezing
Deep Freezer	Storage Freezer

Figure 2.1 Ice cream production equipment used to prepare product for this study

Carpigiani RTX120 | Carpigiani Turbo Mix | Carpigiani LB300G | Blast freezer | Deep Freezer

Methods

This study involved conducting a technical analysis of the ice cream category, designing experimental runs, developing detailed formulations, producing ice cream prototypes, and conducting a consumer study to assess liking and diagnostics of the products developed.

Technical Analysis

Technical analysis in food product development involves systematically gathering and analyzing technical information such as brand, ingredients, nutritional composition, price, claims, etc., for the products available in the market. This helps understand the various attributes and factors that play a role in influencing consumer preferences and market dynamics across different types of products within the category. Such insights enable product development to understand the product category and optimize their products to meet consumer demands and enhance the product's marketability.

In our study, this was achieved using Mintel (market intelligence tool) and direct market visits to collect and analyze the nutritional information of four mainstream flavors (vanilla, chocolate, caramel, and strawberry) in the dessert/ice cream category, in tub-format launched in the United States within the last 5 years. A total of 413 products were selected for analysis with some products containing other ingredients blended such as fudge, brownie, nuts, choco chips, etc., These products were randomly chosen to represent various types of ice cream, including premium options, regular varieties, low-cost alternatives, frozen desserts, and plant-based options.

We observed that higher-priced products tend to have lower overrun and higher fat content. Overrun is the percentage increase in ice cream volume resulting from air incorporated during freezing. However, the difference in added sugar content between high and low-priced items was not evident. The more expensive offerings tend to contain natural ingredients, organic and clean labels, fewer ingredient lists, and premium and authentic flavor components such as Madagascar/Tahitian vanilla extracts and vanilla pod specs. It was observed that nondairy-based desserts had a low overrun ranging from 20% to 60% and were generally priced higher than dairy alternatives.

Analyzing data from 413 frozen dessert products, as shown in Figure 2.2 (scatter plot), revealed a wide variation in sugar and fat content. The added sugar ranged from 7% to 30%, while the fat content varied between 6% and 26%. The red circle shown in Figure 2.2 (scatter plot) indicates that there are few products with sugar content falling within the range of 7% to 14% and fat content ranging from 6% to 13%. This indicates an untapped market for frozen desserts with lower sugar and fat levels. Thus, there is potential for developing frozen desserts/ice creams with less sugar and fat content using natural ingredients (i.e., fruit extracts and powders) as replacers to meet the increasing demand for healthier options in this category.

Figure 2.2 Sugar and fat % (wt./wt.) variations in commercial ice creams sold in the United States market. white space for exploring new products.

Design of Experiments (Optimal Mixture Design) using Statease 360 software

Design of experiments (DOE) is a systematic and statistical approach used in new product development to design the experiments and establish the relationship between factors (i.e., ingredients) that influence a process (i.e., formulation) and the outcomes (i.e., responses) it produces. Experiments are designed to efficiently test interactions between multiple ingredients using a structured approach. DOE includes several types of designs, such as full factorial, fractional factorial, response surface methodology, central composite design, and mixture design. The appropriate method is chosen based on the objectives and constraints of the study. The Mixture design is used to identify the optimal combination of ingredients, ensuring that the sum of all ingredients equals 100%. It is majorly used in food formulations to determine the ideal proportions of ingredients in a formulation, including flavors and additives, to achieve the desired characteristics and quality of the product. Optimal mixture designs are used when the process requires adjustments to the experiment that cannot be accommodated by a standard design. These adjustments could include constraints on the proportions of certain ingredients or the need to explore a specific region of the experimental space.

For our research, we used optimal mixture design as it allows us to achieve the best estimation precision for model parameters and accurately represent the relationship between ingredient proportions and response variables which include appearance liking, overall aroma liking, overall liking, flavor liking, fruit flavor liking, sweetness liking, overall texture liking, mouthfeel liking and aftertaste liking in our formulation process.

Our study aims to design ice cream trial runs by adjusting the combinations and proportions of three key ingredients - sucrose, milk fat, and lucuma fruit powder - along with other filler ingredients (milk, corn solids, nonfat dry milk, and stabilizer) as a base to create formulations that add up to 100%. The goal is to find the best combinations that effectively cover the design space while minimizing the number of trials.

The optimal (custom) mixture design for our study was selected using Statease 360 software, considering unequal ingredient levels, blocking, multiple ingredient constraints, and specific augments. Based on these factors, the run settings are chosen algorithmically for the best estimates of the model. The experiment consists of four components - lucuma fruit powder, sucrose, milk fat, and base(filler), with their limits totaling up to 100%. Point exchange and 0 replicates were selected in our design to minimize the trial runs. Point exchange restricts available runs to a specified candidate set, which is a subset of potential runs meeting certain criteria such as constraints on ingredient proportions or specific regions of the design space.

The Design of experiments was conducted in two phases. Phase 1 involved preliminary lab experiments to better understand the constraints related to ingredient usage, such as determining the optimal upper and lower limits for the key ingredients. Based on the observations from the first phase, the upper and lower limits for key ingredients were established to develop the ice cream formulations in the second phase.

Phase 1 (Setting ingredients limits)

Based on market research, the upper limits for added sugars (sucrose) and fat were fixed at 13% (Wt./Wt.) levels as constraints for our phase 1 experiment. The lower limit for added sugars was set at 6% (Wt./Wt.) with a fat content level of 2% (Wt./Wt.). The composition (added sugars and fat) of the formulation was adjusted using sucrose and milk cream with a fat content of 36%. The upper and lower limits for lucuma fruit powder were set in the range between 0.75 % and 8% (Wt./Wt.). The constraints and limits for phase 1 experiment are shown in Table 2.3. The remaining proportion of the formulation is made up of other ingredients at the same levels, with only the whole milk proportion varying.

Table 2.3 Ingredient limits for phase 1 experiments

Ingredients	Low (%)	High (%)
Fat	2.00	13.00
Sucrose	6.00	13.00
Lucuma fruit powder	0.75	8.00
Base (other ingredients)	77.75	79.00

Note. All the ingredients (%'s) are on Wt./Wt. basis.

With these levels as constraints, 11 trial runs were designed using an optimal mixture design in Statease 360 software for our experiments. The lab-scale experiments were conducted to evaluate the sensory properties and acceptability of 11 ice cream formulations within an internal team of 5 panelists. The goal was to identify if any constraints needed iteration before scaling up.

Based on the panelists' comments and product quality after 60 days of storage at -7.6°F, it was found that the ice cream formulations within the specified constraints need certain modifications before scaling up. It was identified that the products with lower fat content (<6% Wt./Wt.) and high lucuma fruit powder were perceived to be too icy and hard texture. The panelists felt that the lucuma ice cream flavor was too strong, with brown (i.e., coffee notes) becoming overpowering beyond 4% (Wt./Wt.) levels. The panelists perceived a lack of smoothness in the ice cream when higher levels of lucuma fruit powder were used and less flavor at low levels (<2 % Wt./Wt.). Furthermore, it was observed that products with higher lucuma levels developed strong brown notes upon aging at 60 days IN -7.6°F.

Phase 2 (Adjusting ingredient limits and constraints)

Phase 2 involved adjusting the constraints of the ice cream formulations based on feedback and observations from phase 1. The upper and lower limits for added sugars (sucrose) and fat were set between 13.0% and 6% (Wt./Wt.). Lucuma fruit powder was reduced to a maximum of 7% (Wt./Wt.) to address strong flavor and texture issues identified in phase 1 and a minimum of 1.5 % for maintaining the perceivable threshold of lucuma flavor. The adjusted ingredient limits and constraints are shown in Table 2.4 and Table 2.5.

Table 2.4 Ingredient limits for phase 2 experiments

Ingredients	Low (%)	High (%)
Fat	6.00	13.00
Sucrose	6.00	13.00
Lucuma fruit powder	1.50	7.00
Base (other ingredients)	73.00	80.00

Note. All the ingredients (%'s) are on Wt./Wt. basis.

Table 2.5 Ingredient limit constraints

Low (%)	Ingredient/Composition	High (%)
7.50 ≤	Fat + Lucuma	≤ 13.00
7.50 ≤	Sucrose + Lucuma	≤ 14.50

Note. All the ingredients (%'s) are on Wt./Wt. basis.

The base of the formulations were made up of other ingredients at the same levels in all the formulations, varying only the whole milk proportion. A total of 11 lucuma ice cream trial runs (Table 2.6) were designed using an optimal mixture design with Statease 360 software for scale-up for the consumer study.

Table 2.6 Trial runs designed using statease 360

Trial Runs	Fat (%)	Sucrose (%)	Lucuma (%)	Base (%) (other ingredients)
1	9.4	6.6	4.0	80.0
2	6.0	13.0	1.5	79.5
3	6.0	7.9	6.1	80.0
4	12.5	7.8	6.7	73.0
5	7.4	9.6	3.0	80.0
6	10.3	9.9	1.5	78.3
7	9.3	10.3	4.2	76.2
8	13.0	6.0	1.5	79.5
9	13.0	7.4	4.0	75.7
10	10.0	6.0	7.0	77.0
11	12.7	12.8	1.5	73.0

Note. All the ingredients (%'s) are on Wt./Wt. basis.

Lucuma Ice Cream Formulations

The experimental design derived from the Statease 360 software was used to develop 11 ice cream formulations along with nutritional composition and product properties using Tech Wizard formulation software. The nutritional composition of the lucuma ice cream was calculated based on the specifications of the ingredients listed on its label. The lucuma ice cream samples were labeled LIC1-L through LIC5-L, indicating low lucuma levels of 1.5% to 3.0% in the formulation. Samples LIC6-M through LIC8-M had moderate lucuma levels of 4.0% to 4.2%, while LIC9-H through LIC11-H contained high lucuma levels ranging from 6.1% to 7.0%. The labels LIC1 to LIC11 identified the different lucuma ice cream samples. The detailed formulations of the lucuma ice creams are shown in Table 2.7 and the calculated corresponding prototype's composition and properties are shown in Table 2.8. The formulations were used to calculate the required quantity (3.5 gallons each) of ice cream for a consumer study.

Manufacture of Ice creams:

The manufacturing process of the ice creams involves several steps which include lucuma ice cream mix preparation, homogenization, batch freezing, packaging, blast freezing, hardening, and storage. All the equipment and utensils were washed and sanitized before and after each product trial. Carpigiani's pastomaster RTX 120 was used for the production of lucuma ice cream liquid mix which involves the blending of ingredients, heat treatment, cooling, and aging. A 33 lbs. batch mix was prepared for each trial formulation. The lucuma ice cream mix production process involved heating the milk to 104°F while being continuously blended, followed by the addition of a dry mix consisting of sugar, stabilizer, soluble corn solids, and lucuma fruit powder that were mixed together.

Table 2.7 Lucuma ice cream mix prototype codes & formulations

Formulations											
Ingredients (Wt./Wt.)	**LIC1-L**	**LIC2-L**	**LIC3-L**	**LIC4-L**	**LIC5-L**	**LIC6-M**	**LIC7-M**	**LIC8-M**	**LIC9-H**	**LIC10-H**	**LIC11-H**
Fixed ingredients											
Non-Fat Dry Milk	7.90	7.90	7.90	7.90	7.90	7.90	7.73	7.90	7.90	7.90	7.90
Soluble Corn solids	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00
Stabilizers/Emulsifiers	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
Variable ingredients											
Whole Milk	62.22	52.46	48.60	42.07	59.97	44.41	56.25	52.29	62.78	42.40	51.60
Heavy Cream	10.87	23.75	31.50	31.20	15.06	31.87	20.94	20.80	10.82	30.70	22.99
Milk fat (g/100g)*	6.00	10.30	13.00	12.70	7.40	13.00	9.40	9.30	6.00	12.50	10.00
Sucrose	13.01	9.89	6.01	12.83	9.60	7.36	6.61	10.31	7.90	7.81	6.01
Lucuma Fruit powder	1.50	1.50	1.50	1.50	2.97	3.96	3.97	4.20	6.11	6.70	7.00
Total (%)	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

*Note. *Milk fat is contributed from heavy cream. Milk fat is included in the formulation table to represent the fat content in each formulation.*

Table 2.7 Ice cream prototype composition

Properties	LIC1-L	LIC2-L	LIC3-L	LIC4-L	LIC5-L	LIC6-M	LIC7-M	LIC8-M	LIC9-H	LIC10-H	LIC11-H
Milk Fat (g/100g)	6.0	10.3	13.0	12.7	7.4	13.0	9.4	9.3	6.0	12.5	10.0
Calories (cal/100g)	177	202	211	233	182	224	190	204	174	231	204
Total Carbohydrates (g/100g)	25.7	22.5	18.6	25.1	23.5	21.8	21.2	25.0	24.3	24.3	22.9
Total Sugars (g/100g)	21.2	18.0	14.1	20.6	18.1	15.8	15.2	18.9	17.1	16.6	15.1
Added Sugars (g/100g)	14.1	10.9	7.1	13.9	10.9	8.9	8.2	11.9	9.9	9.9	8.2
Dietary Fiber (g/100g)	0.3	0.9	0.9	0.9	1.5	1.9	0.3	2.0	2.8	3.0	3.1
Protein (g/100g)	5.1	5.1	5.2	5.0	5.1	5.1	5.1	5.0	5.1	5.0	5.1
Total Solids (% Wt./Wt.)	38.2	39.4	38.3	44.2	37.7	41.6	37.5	41.0	37.4	43.8	40.2
Non-fat dry milk (% Wt./Wt.)	13.6	13.5	13.6	13.1	13.6	13.3	13.5	13.3	13.6	13.1	13.4
Overrun %	47	51	50	54	51	45	50	46	51	40	41

As the mixture reached 149°F, heavy cream was transferred and further heated with continuous blending until the mix reached a temperature of 194°F and held for 2 minutes. At this stage, the mix was immediately cooled down to 39°F and aged for 4 hours maintained at 39°F with continuous mixing. The required ice cream mix (2 gallons) is then transferred to a clean beaker and mixed at high-speed using Carpigiani Turbo mix at 5000 RPM for 6 minutes to give a homogenization effect.

The mix is then transferred to a Carpigiani LB 302 G batch freezer for the freezing process which is set in ice cream production mode "10" for 30 minutes. The freezing process is set and maintained in similar modes for each production cycle to ensure consistency from one batch to another. The lucuma ice cream produced is then packed in a half-gallon poly-coated paper cup with a lid and blast frozen to below -22°F for 6 hours before being transferred into a deep freezer for storage at -7.6°F until the day of the consumer study.

Central Location Consumer Testing

For the central location test (CLT), one scoop (approximately 2oz) of the sample was served in 4oz disposable polystyrene translucent plastic souffle cups (Dart, Mason, Michigan, USA) covered with clear lids. Sample cups were labeled with random three-digit codes. The questionnaire contained a brief introduction to lucuma fruit ice cream. It explained that lucuma fruit powder is used as a natural sweetener and flavor in ice cream, replacing processed cane sugar. The consumers were presented with the samples in sequential monadic order and were asked to answer the questions based on the sample evaluated. Water was used as a palate cleanser. Figure 2.3 shows the pictures of the prototypes/samples used in the study.

Figure 2.3 Lucuma ice cream samples used in the consumer study

Participant Recruitment

A total of 104 participants (21 males and 83 females) were recruited from the Kansas City area from the consumer database of the Sensory and Consumer Research Center at Kansas State University (Olathe, Kansas, USA). A wide age distribution of participants ranging from 18 years to 65 years was allowed. Consumer demographics are shown in Table 2.8. Consumers had to be willing to try new flavors and would like to consume ice cream flavors such as Vanilla, Butter Pecan, French Vanilla, Caramel/Salted Caramel. Previous research shows that lucuma fruit contains underlying notes of brown flavors such as caramel. Participants should not have taken part in consumer research within the last three months. The study was conducted over 2 consecutive days at the Sensory and Consumer Research Center at Kansas State University, Olathe, Kansas, USA. Participants were compensated for their time.

Table 2.8 Consumer demographics from central location test (n = 104)

Characteristics	Categories	Percentage (%)
gender	male	20
	female	80
age	17 years or younger	0
	18-34 years old	23
	35-50 years old	40
	51-65 years old	37

Questionnaire

Questionnaire informed consent was obtained from the participants before product evaluation. The questionnaire included acceptance questions for the product appearance, aroma, overall flavor, fruit flavor, sweetness, texture, mouthfeel, and aftertaste. Participants were asked to rate their responses using a 9-point hedonic scale (1 = dislike extremely and 9 = like extremely). Additionally, they were asked to evaluate the intensities of fruit flavor and sweetness attributes in the product using a line scale ranging from no sweetness/flavor to extreme sweetness/flavor (Statistically treated as 0 = none and 9 = extreme). A 5-point Just-About-Right (JAR) scale was used to determine product penalties by the consumers for the color attribute. On a 5-point JAR scale, 1 indicated “much too light”, 3 was “just about right” and 5 represented “much too dark”. Check-All-That-Apply (CATA) questions were used to collect the CATA data for assessing the sensory attributes relevant to each prototype based on their product composition. After evaluating 11 products, participants were asked to express their agreement or disagreement with 32 statements regarding their health and taste attitudes using a 7-point scale (1 = strongly disagree and 7 = strongly agree) to understand their attitude towards health and taste preferences. After attitudinal testing participants were asked “How interested would you be in buying lucuma ice cream” on a 5-point scale (1 = definitely will not buy and 5 = definitely will buy) to analyze their purchase intent.

Data Analysis

Analysis of Variance (ANOVA) was performed using Fisher’s least significant difference (Fisher’s LSD) for consumer liking data and intensity ratings. Penalty analysis was conducted on JAR data to evaluate participant penalties and the impact on liking score when a sample characteristic was not rated as just about right. Correspondence analysis was performed on the CATA data to visually demonstrate the variability of the attributes perceived in different lucuma ice cream samples. The data analysis was performed using XLStat software (Addinsoft, New York, USA).

Results and Discussion

Consumer Liking

The consumer liking for all the attributes was significantly different ($p<0.05$) for the lucuma ice cream samples except for aroma liking. This shows a wide variability in consumer liking between the samples. As shown in Table 2.9, samples LIC4-L, LIC1-L, and LIC2-L received the highest mean overall liking scores followed by samples LIC5-L, LIC3-L, LIC8-M, LIC6-M, LIC7-M, and LIC9-M, respectively. Samples LIC11-H and LIC10-H were the least liked by the consumers. The consumer liking of the samples appears to be primarily influenced by the levels of added sugar and lucuma. Products with higher added sugar and lower lucuma levels received the highest overall liking scores, while samples with reduced sugar and increased lucuma content were the least liked by consumers. This indicates that reducing added sugar drastically impacts the consumer's liking negatively while increasing lucuma content does not effectively replace the added sugar in terms of contributing sweetness and decreases the product's liking. The variation in fat levels did not impact the consumer liking significantly.

Table 2.9 Consumer liking results from the evaluation of lucuma ice cream samples on a 9-point hedonic scale (n = 104)

Prototype codes	**Appearance Liking**	**Overall Aroma Liking**	**Overall Liking**	**Flavor Liking**	**Fruit Flavor Liking**	**Sweetness Liking**	**Overall Texture Liking**	**Mouthfeel Liking**	**Aftertaste Liking**
LIC1-L	7.0 a	5.8 a	7.1 a	7.0 a	6.2 a	7.0 a	7.7 a	7.7 a	6.8 a
LIC2-L	6.6 abc	5.7 a	7.0 a	7.1 a	6.1 ab	6.9 a	7.5 a	7.3 a	6.6 a
LIC3-L	6.7 ab	5.7 a	6.1 bc	6.0 bc	5.5 c	5.9 c	6.1 bc	6.2 bc	5.8 b
LIC4-L	6.4 bcde	5.7 ab	7.2 a	7.3 a	6.4 a	7.1 a	7.5 a	7.4 a	6.9 a
LIC5-L	6.4 bcd	5.7 a	6.4 b	6.4 b	5.7 bc	6.4 b	6.6 b	6.6 b	5.7 b
LIC6-M	6.0 efg	5.6 ab	5.6 cd	5.8 c	5.4 c	6.0 bc	5.8 c	5.7 cd	5.1 c
LIC7-M	6.2 cdef	5.5 ab	5.5 d	5.5 c	5.3 c	5.8 c	5.8 c	5.6 d	5.0 c
LIC8-M	6.0 defg	5.6 ab	5.6 cd	5.7 c	5.5 c	5.9 c	6.2 bc	6.1 c	5.3 bc
LIC9-H	5.8 fg	5.4 ab	4.8 e	4.8 d	4.6 d	5.3 d	4.9 d	4.7 e	4.4 d
LIC10-H	5.5 h	5.3 b	4.1 f	4.1 e	4.2 d	5.0 d	4.1 e	4.0 f	4.0 d
LIC11-H	5.7 gh	5.5 ab	4.3 f	4.3 de	4.4 d	5.0 d	4.5 de	4.3 ef	4.2 d
Pr > F(Model)	<0.0001	0.362	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Note. Means with same letter are not significantly different (p>0.05)

Intensity Ratings

Ice cream samples were evaluated for fruit flavor, and sweetness (taste) intensities on a line scale ranging from no sweetness/flavor to extreme sweetness/flavor (Statistically treated as 0 = no and 9 = extreme).

Table 2.10 Intensity scores of lucuma ice cream samples on line scale (n = 104)

Prototype codes	Fruit Flavor Intensity (scale 0 - 9)	Sweetness Intensity (scale 0 - 9)
LIC1-L	3.7 e	5.1 a
LIC2-L	3.7 de	4.6 ab
LIC3-L	2.6 f	3.3 e
LIC4-L	3.8 cde	4.9 a
LIC5-L	4.3 abcde	4.6 ab
LIC6-M	4.3 abcd	4.1 bc
LIC7-M	4.2 bcde	4.0 cd
LIC8-M	4.6 ab	4.6 ab
LIC9-H	4.4 abc	3.8 cde
LIC10-H	4.9 a	3.7 cde
LIC11-H	4.5 ab	3.4 de
Pr > F(Model)	<0.0001	<0.0001

Note. Means with same letter are not significantly different (p>0.05)

Analysis of variance results for average intensity scores are shown in Table 2.10. The mean scores for fruit flavor and sweetness intensities of the lucuma ice cream samples showed significant differences. Sample LIC10-H exhibited the highest fruit flavor intensity, whereas sample LIC3-L had the lowest. The results show that the fruit flavor intensity is driven by both added sugar and lucuma levels. In terms of sweetness intensity, sample LIC1-L received the highest rating while sample LIC3-L scored the lowest. The results indicate that increasing the lucuma content did not effectively enhance the perceived sweetness of the ice cream samples, suggesting that lucuma is unable to fully compensate for the sweetness provided by added sugars.

Table 2.11 Penalty analysis of the Just-About-Right (JAR) scores for the color attribute of lucuma ice creams (n = 104)

Sample code	JAR Levels	% of consumers	Mean drops	Penalty	p-value	Significant
LIC1-L	Too light	16.35%	0.454			
	JAR	83.65%				
	Too dark	0.00%				
LIC2-L	Too light	10.58%	0.611			
	JAR	81.73%				
	Too dark	7.69%	1.997			
LIC3-L	Too light	11.54%	0.051			
	JAR	85.58%				
	Too dark	2.88%	1.801			
LIC4-L	Too light	14.42%	0.016			
	JAR	81.73%				
	Too dark	3.85%	1.782			
LIC5-L	Too light	6.73%	0.286			
	JAR	80.77%				
	Too dark	12.50%	-0.187			
LIC6-M	Too light	10.58%	1.086			
	JAR	53.85%				
	Too dark	35.58%	1.565	0.56	<0.0001	Yes
LIC7-M	Too light	7.69%	0.362			
	JAR	73.08%				
	Too dark	19.23%	1.137			
LIC8-M	Too light	7.69%	1.592			
	JAR	62.50%				
	Too dark	29.81%	1.125	0.34	0.008	Yes
LIC9-M	Too light	6.73%	0.412			
	JAR	50.00%				
	Too dark	43.27%	0.914	0.4	0.021	Yes
LIC10-H	Too light	3.85%	0.659			
	JAR	42.31%				
	Too dark	53.85%	1.516	0.82	0	Yes
LIC11-H	Too light	6.73%	1.72			
	JAR	49.04%				
	Too dark	44.23%	1.102	0.49	0.01	Yes

*Note: JAR ≥ 70% of consumers, *Minimal penalty <0.25, *Moderate penalty 0.25≤ X < 0.50, *High penalty ≥ 0.50, significant (p>0.05)*

The penalty analysis results indicate that samples LIC10-H and LIC6-M received a high penalty and samples LIC11-H, LIC9-M, and LIC8-M received a moderate penalty due to the lucuma ice cream color being too dark. The penalty analysis results indicate that ice cream samples with higher fat content, higher lucuma levels, and low added sugar levels were penalized for being too dark in color. Besides the increase in lucuma fruit powder contributing to the darker color of the ice cream, we have also observed that increasing the fat content of the ice cream enhances its brightness, but it also heightens the likelihood of the color being perceived as too dark.

Check All That Apply (CATA) results

The CATA attributes for the samples were developed based on the open-ended comments from previous research conducted by (Singh, 2022) and from the phase 1 experiment. A total of 17 flavor attributes were included: vanilla, milky, creamy, buttery, ripe fruit, maple syrup, caramel, coffee, butter pecan, nutty, walnut, chocolate, butterscotch, french vanilla, chemical/artificial, overripe fruit and bitter. In addition to these flavor attributes, consumers are asked to specify/describe (open-ended) if they perceive any other flavors in the sample they evaluate.

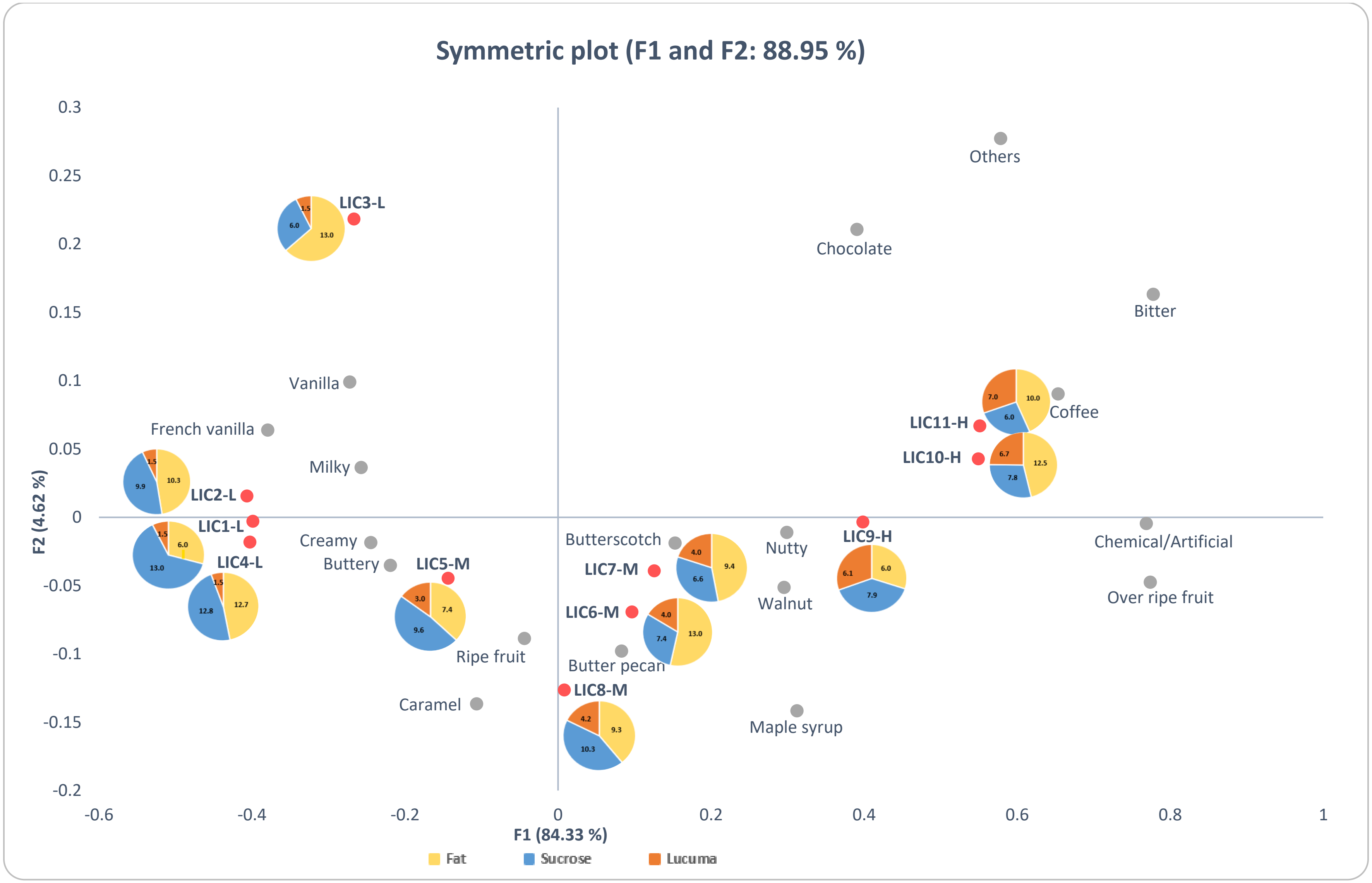
The results were analyzed based on the frequency counts for each sensory term on how often a term was selected for each product. For example, for lucuma ice cream sample LIC4-L, consumers selected the "creamy" attribute 79% of the time, "nutty" 16%, and "Chemical/artificial" 3% whereas for sample LIC10-H, the "creamy" attribute was selected 31% of the time, "nutty" 49%, and "Chemical/artificial" 30%.

Correspondence analysis (CA) was conducted on the CATA data to visualize the relationships between different lucuma ice cream samples and their perceived flavor attributes, taking into account the varying concentrations of lucuma fruit powder, sucrose, and fat across formulations. This approach allows for a more nuanced understanding of how these ingredients interact to influence the flavor profile of the lucuma ice creams.

The symmetric plot of CA (Figure 2.4) revealed distinct patterns, the samples with lower lucuma content (LIC1-L, LIC2-L, LIC3-L, LIC4-L) clustered together, suggesting that they shared a common flavor profile characterized by "vanilla", "french vanilla", "milky", "creamy", and "buttery" notes. The variations in flavor profiles within each group were likely influenced by the differing sucrose and fat ratios across the samples. The reduction in sucrose content in LIC3-L resulted in a decrease in the intensity of certain flavors, such as the creamy and buttery. A slightly bitter flavor was perceived compared to the other low-lucuma samples. LIC1-L, with lower amounts of lucuma, lower fat content, and higher sucrose levels, was reported by the highest number of consumers to be perceived as having a creamy flavor compared to the other lucuma ice cream samples evaluated. This observation may be attributed to the presence of specific volatile compounds identified in lucuma fruit, including δ-octalactone, which is known to contribute a coconut-like, creamy aroma and flavor profile to the fruit (Inga et al., 2019). The presence of diacetyl, in combination with δ-octalactone, may have helped to balance the creamy and buttery flavors in LIC1-L, even though the fat content was reduced compared to LIC4-L. However, further research is needed to confirm the presence of δ-octalactone in lucuma ice cream samples and to better understand its specific contribution to the creamy profile, particularly in low-fat lucuma ice cream formulations.

The ice cream samples with moderate lucuma content, including LIC5-M, LIC6-M, LIC7-M, and LIC8-M, were perceived to have a range of flavors such as "creamy," "nutty," "butter pecan," "ripe fruit," "maple syrup," "walnut," and "caramel." Among the moderate lucuma ice cream samples, LIC5-M is perceived to have "creamy" and "french vanilla" flavors compared to the other moderate lucuma ice cream samples. The samples with high lucuma levels (LIC9-H, LIC10-H, LIC11-H) were perceived with flavors such as “nutty”, “bitter”, “overripe”, “chemical/artificial”, and “coffee”. These insights highlight the importance of optimizing lucuma, sugar, and fat levels to achieve the desired flavor profile in lucuma-based ice creams.

Figure 2.4 Check-All-That-Apply (CATA) analysis for sensory attribute variations in lucuma ice cream samples.



Note: The values in the pie chart represent the percentages of fat, sucrose, and lucuma fruit powder in each lucuma ice cream sample.

Conclusion

Results show a wide variation in lucuma ice cream samples based on the proportion of ingredients used in the formulation. Adjusting the levels of ingredients including lucuma fruit powder, sucrose, and fat in the ice cream formulation significantly affected the sensory properties and consumer liking of the lucuma ice creams. Therefore, the steps described in this chapter succeeded at producing samples with a wide range of sensory characteristics, which will maximize learnings during the next steps of research.

Although certain patterns such as ice cream samples containing lower lucuma powder and high sucrose tend to increase consumer liking, consumer responses to a sample are based on the synergistic effect of multiple ingredients in the formulation. Understanding the interaction of different levels of ingredients in the formulation and their impact on consumer liking is crucial for determining the ideal ingredient proportions. This could help develop a lucuma ice cream product that maximize consumer acceptance and ensures success in the market. Further research will aim to optimize consumer liking scores and determine the ideal ingredient levels in lucuma ice cream.

References

Artisanal Ice Cream Market. (2023, January 1). https://www.coherentmarketinsights.com/insight/artisanal-ice-cream-market-2967/toc

Goff, H D. (2008, July 1). 65 Years of ice cream science. International dairy journal, 18(7), 754-758. https://doi.org/10.1016/j.idairyj.2008.03.006

Goff, H D. (2018, January 1). Ice Cream and Frozen Desserts: Product Types. https://doi.org/10.1016/b978-0-08-100596-5.00833-7

Goff, H D., & Hartel, R W. (2013, January 1). Ice Cream. Springer eBooks. https://doi.org/10.1007/978-1-4614-6096-1

Hartel, R., Rankin, S., & Bradley, R. (2017, December 5). A 100-Year Review: Milestones in the development of frozen desserts.. https://journalofdairyscience.org/retrieve/pii/S0022030217310512

Ice Cream Market in the United States: Market Snapshot to 2020. (2017, February 1). https://www.proquest.com/reports/ice-cream-market-united-states-snapshot-2020/docview/1872816196/se-2

Ice cream trends: Non-dairy and low-sugar NPD soars, but flavor remains key purchasing factor. (2021, July 12). https://www.foodingredientsfirst.com/news/ice-cream-trends-non-dairy-and-low-sugar-npd-soars-but-flavor-remains-key-purchasing-factor.html

Kwak, H S., Meullenet, J., & Lee, Y. (2016, April 18). Sensory profile, consumer acceptance and driving sensory attributes for commercial vanilla ice creams marketed in the United States. Wiley-Blackwell, 69(3), 346-355. https://doi.org/https://doi.org/10.1111/1471-0307.12314

Quinzio, J. (2009, May 5). Of Sugar and Snow: A History of Ice Cream Making. https://www.google.com/books/edition/Of_Sugar_and_Snow/9OEmdcwYhfEC

Rolon, M L., Bakke, A J., Coupland, J N., Hayes, J E., & Roberts, R. (2017, July 1). Effect of fat content on the physical properties and consumer acceptability of vanilla ice cream. Elsevier BV, 100(7), 5217-5227. https://doi.org/https://doi.org/10.3168/jds.2016-12379

Singh, G. (2022, February 8). Sensory and consumer evaluation of lucuma powder as an ingredient for ice cream in the United States

Sipple, L., Racette, C., Schiano, A., & Drake, M. (2022, January 1). Consumer perception of ice cream and frozen desserts in the “better-for-you” category. Elsevier BV, 105(1), 154-169. https://doi.org/https://doi.org/10.3168/jds.2021-21029

Inga, M., García, J M., Aguilar-Galvez, A., Campos, D., & Osorio, C. (2019, January 1). Chemical characterization of odour-active volatile compounds during lucuma (Pouteria lucuma) fruit ripening. Taylor & Francis, 17(1), 494-500. https://doi.org/10.1080/19476337.2019.1593248

Yahia, E M., & Guttierrez-Orozco, F. (2011, January 1). Lucuma (Pouteria lucuma (Ruiz and Pav.) Kuntze). Elsevier BV, 443-450e. https://doi.org/https://doi.org/10.1533/9780857092885.443

Chapter 3 - Sensory optimization of Peruvian Lucuma fruit ice cream using I-Optimal Mixture Design

Abstract

The variability of sensory and consumer data makes it difficult to accurately evaluate and model consumer liking scores when developing a new product. When working within a formulation, an effective method to overcome this challenge is through I-Optimal mixture design. This technique allows us to understand the interactions between the ingredients and their impact on consumer acceptance by optimizing the independent variables based on consumer liking scores. The research objective was to determine the optimal formula for lucuma ice cream by using an I-Optimal mixture design to model consumer acceptance scores. The analysis was completed using Scheffe Linear Mixture Model. Lucuma fruit powder, milk fat, and sucrose were chosen as the independent variables, with additional ingredients serving as the filler. Lucuma fruit powder was used within the range of 1.5% to 7.0%, while both milk fat and sucrose ranged from 6.0% to 13.0% in the liquid mix of the ice cream formulation. As determined by the mixture design, a total of 11 lucuma ice creams were developed and tested with n=104 consumers. Consumer testing was conducted over two days using a completely balanced randomized design.

The consumer acceptance scores were used to predict the optimal levels of ingredients required in the lucuma ice cream formulations. By optimizing the overall liking scores of consumers, the predicted optimal levels for lucuma fruit powder, sucrose, and milk fat are 1.5%, 13%, and 6.0%, respectively with an overall likeability score of 7.3.

The study indicates that reducing sucrose and increasing lucuma fruit powder in the formulation leads to decreased consumer acceptance. It is important to highlight that incorporating

lucuma fruit powder at optimal levels in the ice cream formulation can enhance the texture of reduced-fat ice cream products.

Introduction

The ice cream sector in the U.S. is adapting to significant shifts in consumer behavior, with wellness, distinctive flavors, and cultural variety as key influences. Producers are introducing healthier choices such as low-fat and dairy-free options while incorporating health-focused ingredients such as vitamins, prebiotics, and probiotics into their products to meet the growing demand for nutritious yet indulgent treats (Ice Cream Market in the United States: Market Snapshot to 2020, 2017).

Cultural immersion through flavor is an emerging trend in the ice cream industry, offering consumers a sensory experience with internationally inspired flavors that go beyond traditional tastes. This allows people to connect with various world cultures through ice cream (Ice Cream Market in the United States: Market Snapshot to 2020, 2017).

These evolving trends create opportunities for growth and creativity in the industry, leading to a shift towards alternative ingredients driven by health-focused consumer demand. Manufacturers are incorporating alternative ingredients such as plant-based milk substitutes and natural sweeteners to meet consumer demand from lactose-intolerant and vegan demographics (Ice cream trends: Non-dairy and low-sugar NPD soars, but flavor remains key purchasing factor, 2021).

Lucuma, scientifically called Pouteria lucuma and belonging to the Sapotaceae family, is a subtropical fruit that comes from the Andean region of South America. The fruit is rich in sugars, fiber, and antioxidants (García-Ríos et al., 2020). The fruit contains a flavor profile with hints of sweet potato, butterscotch, and maple syrup, making it popular for use in sweet desserts (Ramberg, 2022).

Lucuma fruit is processed into frozen pulp and flour for long-term storage and convenient use in culinary applications, preserving its nutritional qualities and extending shelf life (Asmat-Campos et al., 2019).

Adding lucuma fruit powder to desserts, such as ice cream, imparts a distinct flavor and aroma while boosting the nutritional value of its inherent antioxidants and fiber. Additionally, it adds natural sweetness and enhances the texture of the ice cream.

Previous research (Singh, 2022) has shown that adding lucuma fruit powder at 5% in ice creams can impact color and texture, leading to chalkiness and graininess that may reduce overall consumer liking.

Successful product development in today's consumer-driven markets relies heavily on using optimization techniques, particularly in the field of food product innovation. Optimization plays a crucial role in improving product attributes such as taste, texture, and shelf life, as well as in ensuring cost-effective production and efficient resource utilization. By employing statistical optimization methods, companies can align their products with consumer preferences, gaining a competitive advantage in the market. The focus in the industry has shifted towards balancing complex flavor profiles, nutritional value, and sensory appeal while also emphasizing cost-effectiveness and sustainability. Optimal mixture design stands out as a sophisticated approach that explores ingredient synergies and proportions to enhance overall product quality. With tools such as Design Expert software from Stat-Ease Inc., product developers can utilize Optimal Mixture design for detailed analysis and prediction of regression equations, enabling them to anticipate product success even before production. Additionally, DFA analysis within the same software suite offers a comprehensive evaluation of multiple quality criteria simultaneously, resulting in a composite desirability score. This integrated approach ensures that each product variant not only meets but surpasses market standards, resonating with consumers and establishing a strong position in the competitive landscape of product offerings.

Irfan et al., (2022) investigated the ideal blend for a mixed fruit juice using black mulberry and canistel. The research employed mixture design and Design Expert software, to optimize the formula based on chemical, physical, and sensory analyses. The study identified a blend with the highest desirability, indicating its potential as a nutritious and flavorful beverage.

Our focus in this research is to develop a balanced lucuma ice cream formulation by optimizing the amount of lucuma powder for both flavor and texture using consumer responses.

Materials and methods

Lucuma Ice Cream Samples

A total of 11 lucuma ice creams were developed using optimal mixture design by varying the proportions of key ingredients including lucuma fruit powder, milk fat and sucrose along with base (other ingredients) which adds to 100% of lucuma ice cream liquid mix. The upper limit and lower limits for sugar and fat were fixed at 13 % and 6 % (Wt./Wt.), respectively. Lucuma fruit powder ranged between 1.5 % and 7 % (Wt./Wt.). The ice creams were manufactured at the Incubator Innovation Kitchen, Kansas State University - Olathe campus using Carpigiani ice cream equipment and stored in a deep freezer at -7.6°F for 25 days before being subjected to the consumer study. A Central Location Test (CLT) was conducted at the Sensory and Consumer Research Center at Kansas State University, Olathe. A complete randomized design was followed and a total of 104 regular ice cream consumers participated in the study. One scoop (2oz) of the sample was served in 4oz translucent plastic cups, labeled with a 3-digit code, and covered with clear lids. The samples were served at 10°F in a sequential monadic order with 60-second intervals between each sample.

Compusense software was used to screen participants and collect data on the acceptance and sensory profiles of the prototypes evaluated by the participants. Analysis of Variance (ANOVA) was performed using Fisher's Least Significant Difference (LSD) for consumer liking Data. The data analysis was performed using XLStat statistical software (Addinsoft, MS Excel, NY, USA). Acceptance scores were used for optimization and prediction of optimum levels of ingredients to develop lucuma ice cream with the maximum acceptance. Previous research conducted by (Kwak et al., 2016) shows that attributes such as overall liking, texture liking, and mouthfeel liking play an important role in consumer acceptance of ice cream. In this study, response variables overall liking, texture liking, and mouthfeel liking were used for predicting the optimal formulation for lucuma ice cream.

Optimization of Lucuma Ice Cream

Optimization aims for the best outcome within given constraints or objectives. In food product development, scientists use different experimental designs to improve product formulations or processes. Mixture designs, introduced by Claringbold in 1955, focus on combining ingredients effectively to reach desired outcomes. Similar to other experimental designs such as Box-Wilson and Box-Behnken, mixture designs aim to create the best combination of ingredients to fulfill particular objectives.

Lucuma fruit powder, sucrose, and milk fat were the three independent variables used in the experimental design, with additional ingredients serving as base (filler). The study aims to optimize the dependent variables (consumers liking scores) to maximize sensory acceptability. Eleven lucuma ice creams were developed using varying levels of lucuma fruit powder, milk fat, and sucrose based on the optimal mixture design. In these experiments, the levels of each variable are interrelated and constrained. In this case, the total amount of all variables in the mixture must add up to 100% (Scheffe 1958; Cornell 1990). The minimum and maximum ranges of all three independent variables are provided for the experimental design.

In situations where a response variable is impacted by multiple independent variables, denoted as

$$\Phi_i (i = 1, 2, 3 \ldots)$$

and the relationship can be represented as

$$\bigcap = f\ (\Phi_1, \Phi_2, \Phi_3)$$

where ∩ denotes the response variable. The complexity of this equation often poses challenges to its practical application. To simplify this complexity, the unknown function "f" is typically approximated using more straightforward empirical functions, such as Scheffe's model.

The expected value of the response variable can be expressed as,

$$E(Y) = \Sigma B_i + \Sigma B_{ij} X_i X_j$$

In this equation:

- $B_i\ X_i$ represents the contribution of independent variables to the response, where B_i serves as the linear coefficient.
- $B_{ij}\ X_i\ X_j$ indicates the response resulting from the synergistic effects of binary mixtures, with B_{ij} representing the quadratic coefficient.

It is essential to note that both the independent variables and the interactions between binary mixtures are vital for estimating the coefficients of the quadratic model. In this formulation, the linear component and the interactions between pairs of ingredients collectively contribute to the overall expected value of the response variable. By incorporating these elements into the quadratic model, researchers can effectively capture the complex relationships and synergistic effects present in the system under investigation.

Desirability Function Analysis (DFA)

In traditional graphical methods, predictive models are employed to visually represent overall responses in optimization studies. Surfaces and contour plots are utilized to predict optimal regions by overlaying them, enabling the simultaneous optimization of all responses or the fulfillment of specific criteria (Khuri and Cornell, 1987; Floros and Chinnan, 1988). An alternative approach involves overlaying contour plots for each response, although this method often necessitates numerous trial-and-error iterations to identify the optimal conditions. Optimization tasks involving multiple variables can also be addressed using a modified version of Harrington's desirability function (Harrington, 1965), integrated with response surface methodology to create a technique known as "desirability optimization methodology" (Derringer, 1994). While this methodology has been in use for over two decades, its implementation has historically been laborious, requiring expertise in experimental design, regression analysis, optimization techniques, and graphical interpretation.

The standard procedure involves converting each response variable y_n into an individual desirability function d_n that ranges from 0 to 1. In this context, if the response aligns with the target or goal, the desirability function d_n equals 1; conversely, if the response falls outside an acceptable range, d_n is set to 0. Each response is then standardized into desired functions d_n using a specific formula.

$$d_n = h_n(y_n)$$

Derringer and Suich (1980) introduced a modified desired function that assigns values based on predefined constraints,

$$0 \text{ if } \quad y_n < a$$

$$d_n = \left(\frac{y_n - a}{b - a}\right)^s \quad \text{if} \quad a \leq y_n \leq b$$

$$\text{If } \; y_n > b$$

where constants "a" and "b" represent the limits of the response, and "s" is a positive constant. By aggregating individual desirability functions into a total desired function "D" (ranging from 0 to 1), researchers can evaluate the overall desirability of the system.

$$D = (d_1, d_2, \cdots d_n)^{1/n}$$

A higher *D* value indicates a more desirable and optimal solution, guiding the determination of factor values that maximize the composite desirability score.

Through the optimization process guided by DFA, researchers can efficiently navigate the complex parameter space, identify the optimal combination of input variables, and develop products that excel in all desired attributes simultaneously.

Data analysis

The mean scores of individual dependent sensory attributes based on consumer liking were calculated and entered in the response variable column for the corresponding trials designed using Statease 360 software. Statease 360 analyzes data using ANOVA to detect significant differences in the response variables. A *p*-value < 0.05 indicates that there is a significant difference between the samples for the particular response variable which is essential for predicting the best formula.

Statease 360 processes all response variables according to specific criteria to identify multiple optimal formulas. The desirability value, which ranges from 0 to 1, indicates the proximity of a formula to its optimum state. A desirability value closer to 1 facilitates the attainment of the best point based on the response variable. This aids in selecting the most efficient formula for the given scenario.

Results and Discussions

Overall Likeability

The overall likeability attribute for each formula was analyzed and the summary statistics are presented in Table 3.1. The analysis of variance (ANOVA) indicates that the p-value of the F-Test in the linear model is <0.0001, signifying that the overall likeability attribute across the 11 formulations is significantly different.

Table 3.1 Statistical summary of overall likeability

Analyzed components	**Result**
Mean	5.79
Standard Deviation	0.2103
Model	Linear Mixture
Sequential p-value	<0.0001
R-Square (R^2)	0.9739
Adjusted R^2	0.9627
Predicted R^2	0.9031
Mathematical Model Equations	6.15*Fat + 7.95 * Sucrose + 0.8428* Lucuma + 6.56 * Base

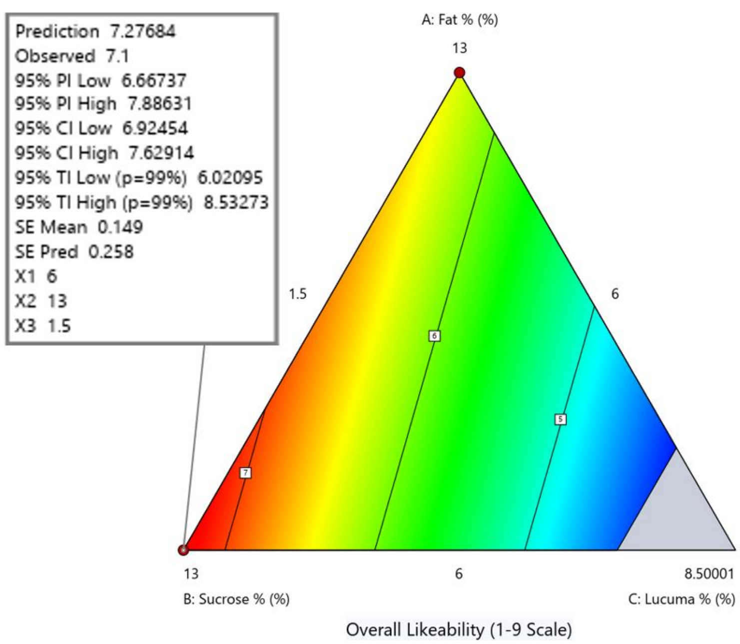
The regression analysis (Table 3.1) reveals an R^2 value of 0.9739, suggesting that the independent variables lucuma fruit powder, milk fat, and sucrose collectively account for 97.39% of the variation in overall likeability. The high R^2 values in the predicted equation for various attributes demonstrate the accuracy of the fitting.

Figure 3.1 illustrates the distribution of overall likeability, the formulas with the highest overall likeability scores are depicted in the red area, followed by orange, yellow, and green, and progressing to light to dark blue, indicating varying levels of overall likeability response.

Based on the contour plot (Figure 3.1) and the mathematical model of the overall likeability response variable using the linear model, it can be observed that the area on the graph is linearly distributed indicating that there is no interaction between the independent variables.

The contour plot (Figure 3.1) shows that an increase in lucuma fruit powder and a decrease in sucrose impacted the consumer acceptance of lucuma ice cream which could be because of a reduction in sweetness. This shows that the addition of lucuma fruit powder does not significantly replace sucrose. Higher levels of lucuma fruit powder contribute to a bitter taste, and artificial and strong flavor notes which could have impacted the consumer liking, also confirmed by CATA analysis results. Overall, high consumer acceptance of lucuma ice creams is linked to high sucrose content (sweetness), lower fat, and lower levels of lucuma fruit powder. Interestingly, reducing the fat content in lucuma ice cream formulations does not affect consumer liking scores.

Figure 3.1 Contour plot graph of overall likeability



Note: X1-Fat, X2-Sucrose, X3-Lucuma powder (% Wt./Wt.).

Overall Texture Liking

The overall texture liking attribute for each formula was analyzed and the summary statistics are presented in Table 3.1. The analysis of variance (ANOVA) indicates that the p-value of the F-Test in the linear model is <0.0001, signifying that the overall texture likeability attribute across the 11 formulations is significantly different.

The regression analysis (Table 3.2) reveals an R^2 value of 0.9596, suggesting that the independent variables lucuma fruit powder, milk fat, and sucrose collectively account for 95.96% of the variation in liking of the overall texture. The high R^2 values in the predicted equation for various attributes demonstrate the accuracy of the fitting.

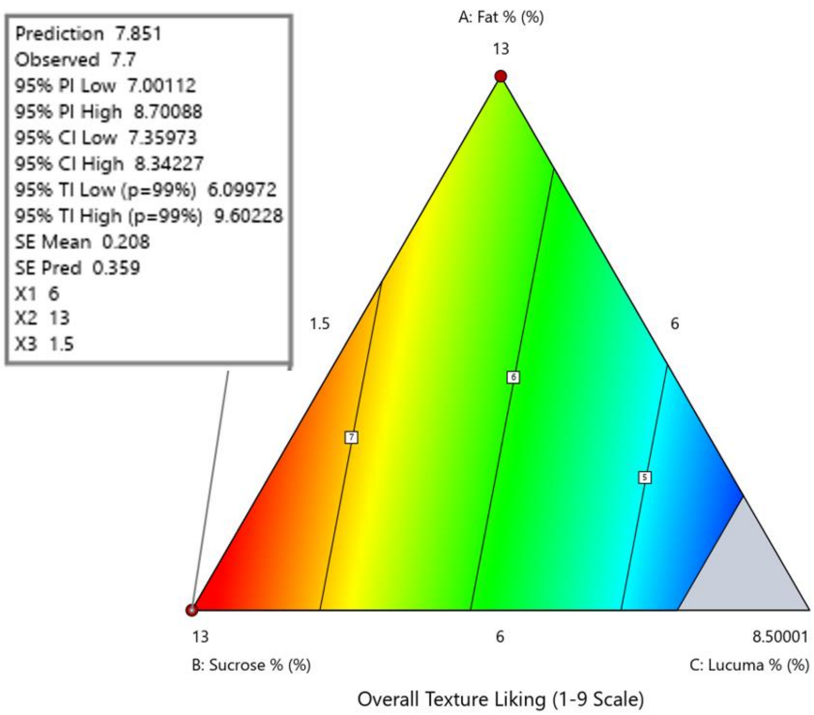
Table 3.2 Statistical summary of overall texture liking

Analyzed components	**Result**
Mean	6.06
Standard Deviation	0.2933
Model	Linear Mixture
Sequential p-value	<0.0001
R-Square (R^2)	0.9596
Adjusted R^2	0.9423
Predicted R^2	0.8546
Mathematical Model Equations	6.14*Fat + 8.80 * Sucrose + 0.8909* Lucuma + 6.83 * Base

Based on the contour plot (Figure 3.2) and the mathematical model of overall texture response variable using linear model, it can be observed that the area on the graph is linearly distributed indicating that there is no interaction between the independent variables

The contour plot (Figure 3.2) shows that as the amount of lucuma fruit powder increases, the overall texture liking score decreases. This may be because of the grainy and powdery texture that develops when using higher amounts of lucuma fruit powder. The overall texture liking scores are higher at 1.5% levels of lucuma fruit powder, which improves the ice cream's texture despite reducing its fat content. These findings emphasize how incorporating optimal levels of lucuma fruit powder in ice cream formulation can enhance the texture of reduced-fat ice cream products.

Figure 3.2 Contour plot graph of overall texture liking



Note: X1-Fat, X2-Sucrose, X3-Lucuma powder (% Wt./Wt.).

Mouthfeel Liking

The mouthfeel liking attribute for each formula was analyzed and the summary statistics are presented in Table 3.3. The analysis of variance (ANOVA) indicates that the p-value of the F-Test in the linear model is <0.0001, signifying that the overall likeability attribute across the 11 formulations is significantly different.

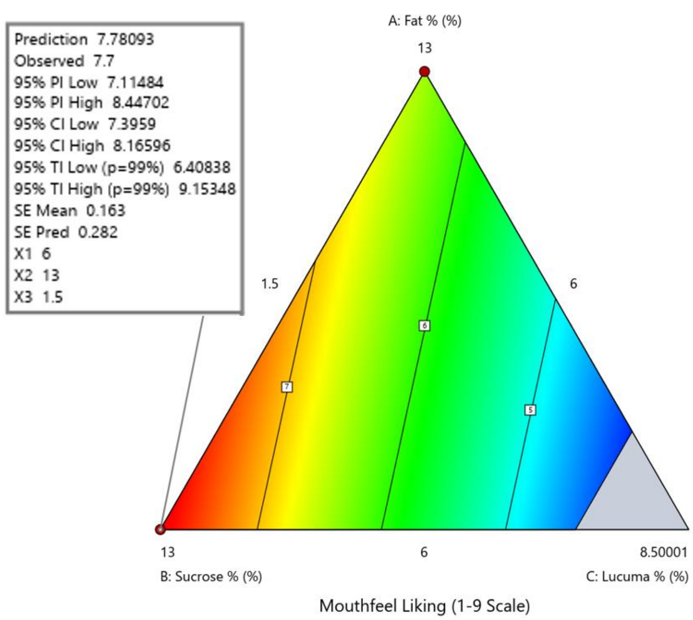
Table 3.3 Statistical summary of mouthfeel liking

Analyzed components	Result
Mean	5.96
Standard Deviation	0.2299
Model	Linear Mixture
Sequential p-value	<0.0001
R-Square (R^2)	0.9765
Adjusted R^2	0.9665
Predicted R^2	0.9198
Mathematical Model Equations	6.13*Fat + 8.70 * Sucrose + 0.4873* Lucuma + 6.80 * Base

The regression analysis (Table 3.3) reveals an R^2 value of 0.9765, suggesting that the independent variables lucuma fruit powder, milk fat, and sucrose collectively account for 97.65% of the variation in overall texture liking. The high R^2 values in the predicted equation for various attributes demonstrate the accuracy of the fitting.

Figure 3.3 illustrates the distribution of Mouthfeel liking, it shows a similar pattern towards overall texture liking.

Figure 3.3 Contour plot graph of mouthfeel liking



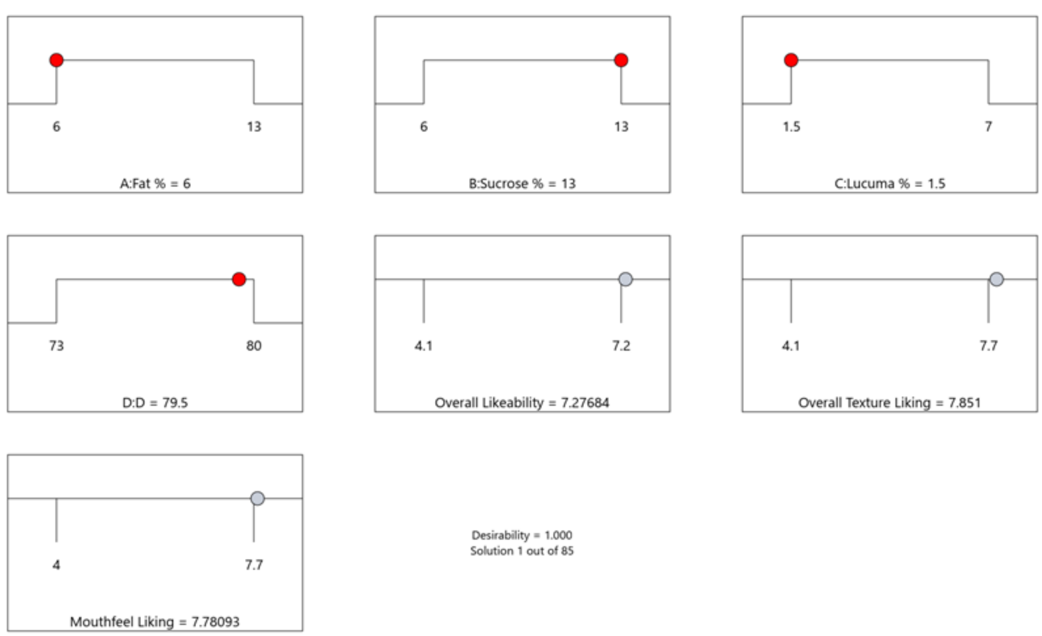
Note: X1-Fat, X2-Sucrose, X3-Lucuma powder (% Wt./Wt.).

Optimization DFA

The DFA was utilized for the simultaneous optimization of lucuma ice cream, where desirability values range from 0 to 1. A value of zero (0) signifies no desirability, while a value of 1 indicates the highest possible desirability within the set constraints. In this study, four crucial quality indicators were chosen for optimization, with constraints established accordingly. These constraints were determined based on their impact on the product, ensuring optimal quality. Therefore, desirable scores were selected to enhance product quality.

The outcomes, depicted in Figure 3.4, indicate that lucuma ice cream prepared by incorporating 1.5% lucuma fruit powder, 6% milk fat, and 13% sucrose with an Overall Likeability score of 7.3, Overall Texture Liking score of 7.9 and Mouthfeel Liking score of 7.8, resulting in a desirability score of 1. The lucuma ice cream produced using optimization techniques was well-received, showcasing high acceptability.

Figure 3.4 Desirability function analysis



Conclusion

The optimal formulation derived by Statease 360, achieving a desirability score of 1.0 through the optimal mixture design approach, resulted in a high acceptability score of 7.3 for overall liking. This was achieved by incorporating 1.5% lucuma fruit powder, 6% milk fat, and 13% sucrose (Wt./Wt.) in the ice cream liquid mix formulation. The study indicates that reducing sucrose and increasing lucuma fruit powder in the formulation leads to a decrease in consumer acceptance. It is important to highlight that incorporating lucuma fruit powder at optimal levels in the ice cream formulation can enhance the texture of reduced-fat ice cream product. Further research will focus on segmenting the consumer base (n=104) using psychographic data to tailor the lucuma ice cream formulations for different consumer groups. This approach helps to align the product with particular consumer attitudes and perceptions, fostering higher consumer satisfaction and success rate in the market.

References

Asmat-Campos, D., Carreño-Ortega, Á., & Díaz-Pérez, M. (2019, February 21). Recovering-Innovation-Exportation Triangle as an Instrument for Sustainable Development: Proposal for Peruvian Agro-Export Development. Sustainability, 11(4), 1149-1149. https://doi.org/10.3390/su11041149

Claringbold, P. J. (1955). Use of the simplex design in the study of joint action of related hormones. Biometrics, 11, 174–185.

Derringer G. 1994. A balancing act: optimizing a product's properties. Qual Prog 27:51–8.

Derringer G, Suich R. 1980. Simultaneous optimization of several response variables. J Qual Technol 12(4):214–9.

Floros JD, Chinnan MS. 1988. Computer graphics assisted optimization for product and process development. J Food Technol 42(2):72–8.

García-Ríos, D., Aguilar-Galvez, A., Chirinos, R., Pedreschi, R., & Campos, D. (2020, April 15). Relevant physicochemical properties and metabolites with functional properties of two commercial varieties of Peruvian<i>Pouteria lucuma</i>. Wiley-Blackwell, 44(6). https://doi.org/https://doi.org/10.1111/jfpp.14479

Harrington EC. 1965. The desirability functions. Ind Qual Control 21(10):494–98.

Ice Cream Market in the United States: Market Snapshot to 2020. (2017, February 1). https://www.proquest.com/reports/ice-cream-market-united-states-snapshot-2020/docview/1872816196/se-2

Irfan, Y., Taufik, Y., & Achyadi, N S. (2022, December 1). Formula Optimization of Black Mulberry and Canistel Mixed Juice using Mixture D-Optimal from Design Expert Software. , 81-95. https://doi.org/https://doi.org/10.25139/fst.vi.4936

Khuri, A.L. and Cornell, J.A. (1987) Response Surfaces: Designs and Analyses. Marcel Dekker Inc., New York.

Kwak, H S., Meullenet, J., & Lee, Y. (2016, April 18). Sensory profile, consumer acceptance and driving sensory attributes for commercial vanilla ice creams marketed in the United States. Wiley-Blackwell, 69(3), 346-355. https://doi.org/https://doi.org/10.1111/1471-0307.12314

Ramberg, E. (2022, January 4). Compositional analysis of the Andean fruit Pouteria Lucuma A comparison of different physical forms (powder, frozen pulp, and fresh pulp)

Singh, G. (2022, February 8). Sensory and consumer evaluation of lucuma powder as an ingredient for ice cream in the United States

Chapter 4 - Developing Lucuma Ice Cream for Diverse Consumer Preferences

Abstract

As companies expand, the diversity of their consumer base increases. Companies can no longer adopt a one-product-fits-all approach to their consumers. Segmenting the consumer base provides a way to classify consumers into more precise categories, enabling companies to gain deeper insights and develop products according to the distinct requirements of each group effectively. This study investigated the development and optimization of lucuma ice cream formulations using an optimal mixture design approach. Lucuma is a starchy fruit with some health benefits, native to the Andean valleys of Peru, Bolivia, Ecuador, and Chile. The objective was to develop an optimized lucuma ice cream formula based on the sensory preferences of health-oriented, and indulgent consumer segments using a Scheffe linear model. The independent variables selected were lucuma fruit powder, milk fat, and sucrose, with other components acting as a filler within the ice cream liquid mix formulation (Wt./Wt.). The proportion of lucuma fruit powder varied from 1.5% to 7.0%, both milk fat and sucrose were adjusted between 6.0% and 13.0% in the ice cream liquid mix. Following the design, a total of 11 different lucuma ice cream formulations were developed and evaluated by 104 consumers. A central location consumer test was conducted over two days using a complete balanced randomized design. The participants were segmented into two groups, health-oriented (n=53), and indulgent (n=51) based on their psychographic data using the health and taste attitudinal scale (HTAS) developed by Roininen, Lähteenmäki, and Tuorila (1999) to measure the importance of health and taste aspects of foods in the food choice process. A k-means clustering technique was used to differentiate consumers according to their agreement with health consciousness statements. The consumer acceptance

scores of each segment were used to predict the optimal levels of ingredients for the lucuma ice cream formulations specific to each segment. Health-oriented consumers had an optimized score of 7.6 on a 9-point hedonic scale, while indulgent consumers scored 7.1 for the same formulation containing 1.5% lucuma fruit powder, 13% sucrose, and 6.0% fat, indicating a difference in their liking pattern. The results show that health-conscious consumers perceived the prototypes as sweeter than indulgent consumers. This suggests that ice cream targeting the health-consumer market could be formulated with less sweetness (added sugar), maintaining taste while offering a healthier profile. The research also indicates that health-oriented consumers are more accepting of higher lucuma levels in ice cream formulations compared to the indulgent consumer segment. The overall liking scores for the lucuma ice cream prototypes with high and low-fat content showed no significant difference for both health-conscious and indulgent consumer segments, indicating that incorporating lucuma fruit powder can help reduce fat in ice creams without impacting consumer satisfaction. It is evident that the evaluated prototypes offer healthier alternatives without affecting consumer acceptance.

Introduction

The US ice cream industry is transforming to meet evolving consumer preferences. Consumers are seeking healthier options, unique flavors, and cultural diversity. Producers are responding with low-fat, dairy-free, and nutrient-rich options (Ice Cream Market in the United States: Market Snapshot to 2020, 2017). The industry embraces cultural immersion through internationally inspired flavors. Lucuma, a subtropical fruit from the Andes, is gaining popularity as a natural sweetener and flavor enhancer in desserts. Processed into frozen pulp and powder, lucuma retains its nutrients and shelf life. It enhances desserts, such as ice cream, with unique flavor, antioxidants, fiber, and natural sweetness.

Singh, (2022) conducted a study on the sensory and consumer evaluation of ice cream incorporating different lucuma fruit powders, among United States consumers. The study revealed a significant purchase interest in lucuma fruit-flavored ice cream. The study highlighted that adding 5% lucuma fruit powder to ice creams affected the color and texture, potentially leading to undesirable characteristics such as chalkiness and graininess, which may impact the overall consumer acceptance. The maximum overall likeability achieved for the lucuma ice cream was 6.5. This led to the current research work, optimizing the key ingredients such as lucuma fruit powder, sucrose, and milk fat in lucuma fruit ice cream to maximize consumer liking.

The optimal formulation derived using statistical tools (Statease 360), achieving a desirability score of 1.0 through the optimal mixture design approach, resulted in a high consumer acceptability score of 7.3 for overall liking (n=104). The research indicates that a reduction in sucrose and an increase in lucuma fruit powder in the formulation results in decreased consumer acceptance.

The food industry thrives on understanding consumer behavior, anticipating trends, and tailoring products to meet diverse needs. While demographic data provides a basic understanding of consumer groups, it often falls short of capturing the nuanced motivations and preferences driving purchasing decisions. This is where psychographic segmentation emerges as a powerful tool, delving into the values, attitudes, and lifestyles influencing consumer choices.

Research by (Bae et al., 2010) effectively segmented Korean consumers based on their food-related lifestyles using K-means clustering on psychographic data. By identifying distinct groups such as "tradition seekers" and "convenience seekers," the study demonstrated how understanding psychographic profiles can reveal valuable insights into consumer behavior, enabling businesses to develop more effective marketing campaigns and tailor products to specific segments.

Another research conducted by (Saba et al., 2019) reveals that consumers prioritize health and taste differently when choosing food. Segmenting consumers by their health interests reveals distinct preferences for food types and information. This highlights the need to tailor food-related strategies to specific consumer segments for maximum effectiveness.

This study aims to utilize psychographic data from 104 consumers using HTAS to segment them based on their health-conscious and indulgent food choices through k-means clustering. The goal was to optimize consumer responses within each segment to develop an ideal lucuma ice cream for each group.

Materials and methods

Lucuma Ice Cream Samples

A total of 11 lucuma ice creams were developed using optimal mixture design by varying the proportions of key ingredients including lucuma fruit powder, milk fat and sucrose, and base (other ingredients) which add to 100% in lucuma ice cream liquid mix. The upper limits and lower limits for sugar and fat were fixed at 13% and 6% (Wt./Wt.), respectively. Lucuma fruit powder ranged between 1.5% and 7% (Wt./Wt.). The ice creams were manufactured in the Incubator Innovation Kitchen, at Kansas State University - Olathe campus using Carpigiani ice cream equipment and stored in a deep freezer at -7.6°F for 25 days before being subjected to the consumer study. A Central Location Test (CLT) was conducted in the Sensory and Consumer Research Center at Kansas State University, Olathe. A complete randomized design was followed and a total of 104 regular ice cream consumers participated in the study. One scoop (2oz) of the sample was served in 4oz translucent plastic cups, labeled with a 3-digit code, and covered with clear lids. The samples were served at 10°F in sequential monadic order with 60-second intervals between each sample.

Compusense software was used to screen participants and collect data on the acceptance and sensory profiles of the prototypes evaluated by the participants. The questionnaire included psychographic questions to measure health and taste attitudes, food-related lifestyles, food habits, and preferences using the Health and Taste Attitudinal scales (HTAS) to segment the consumers.

Analysis of Consumer attitudes towards health and taste of foods

The Health and Taste Attitude Scales by (Roininen et al., 1999) were used to measure food-related attitudes. This study included 3 sub-scales related to General Health interest with eight statements, which reflects a general interest in healthy eating; Light product interest with six statements determining the preference for low-fat or low-sugar products; and natural product interest with six statements, related to an interest in consuming unprocessed food without additives. In addition, there were two taste-related sub-scales: the first included six statements to assess the intensity of sweet food cravings, while the second, with another six statements, evaluated the use of food as a reward. Each sub-scale featured an even distribution of statements framed both positively and negatively. All the statements were scored on a seven-point category scale with the scales labeled from "strongly disagree" to "strongly agree". The data was standardized within each participant to minimize the effect of individual scale usage differences.

Segmentation

The consumers were segmented using a K-Means clustering, based on the mean scores of the five sub-dimensions of the health and taste sections of the HTAS questionnaire. K-means clustering is commonly used in consumer behavior analysis to group individuals based on their attitudes towards health and taste preferences, as measured by the Health and Taste Attitude Scales data. (Bae et al., 2010) used K-means clustering on survey responses to segment consumers into "tradition seekers" and "convenience seekers," revealing distinct dietary preferences and shopping behaviors. This method aims to segment the population into distinct clusters by iteratively assigning each individual to the cluster with the nearest mean. The K-means algorithm follows two main steps: assigning data points to the nearest cluster and updating cluster centroids based on the mean of data points in each cluster. This process continues until convergence, where cluster assignments stabilize. This effectively groups individuals with similar attitudes, such as healthy and indulgent food preferences, together.

Once the consumers are segmented into health-conscious and indulgent groups based on their attitudes, their sensory responses to key attributes are utilized to optimize and predict the ideal ingredient levels for developing lucuma ice cream that maximizes acceptance within each segment. Previous research by (Kwak et al., 2016) indicates that attributes such as overall liking, texture liking, and mouthfeel liking play a crucial role in consumer acceptance of ice cream. In this study, the response variables of overall liking, texture liking, and mouthfeel liking were employed to predict the optimal formulation for lucuma ice cream for both segments.

Optimization of Lucuma Ice Cream

Optimization aims for the best outcome within given constraints or objectives. In food product development, scientists use different experimental designs to improve product formulations or processes. Mixture designs, introduced by Claringbold in 1955, focus on combining ingredients effectively to reach desired outcomes. Similar to other experimental designs such as Box-Wilson and Box-Behnken, mixture designs aim to create the best combination of ingredients to fulfill particular objectives.

Lucuma fruit powder, sucrose, and milk fat were the three independent variables used in the experimental design, with additional ingredients serving as base (filler). The study aims to optimize the dependent variables (consumers liking scores) to maximize sensory acceptability. 11 lucuma ice creams were developed using varying levels of key ingredients such as lucuma fruit powder, milk fat, and sucrose based on the optimal mixture design. In these experiments, the levels of each variable are interrelated and constrained. In this case, the total amount of all variables in the mixture must add up to 100% (Scheffe 1958; Cornell 1990). The minimum and maximum ranges of all three independent variables are provided for the experimental design.

Data analysis

The K-means clustering method (XLStat software, Addinsoft, New York, USA) was used to analyze the standardized scores of the 5 HTAS subscales, aiming to identify consumer segments based on their attitudes towards health and taste. Based on the Silhouette scores, a two-cluster solution was identified as optimal. This led to the identification of two distinct clusters: health-conscious consumers (n = 53) and indulgent consumers (n = 51). Analysis of variance (ANOVA) showed a significant difference between these segments with a p-value less than 0.05.

The consumer liking mean scores of the sensory attributes were analyzed for each segment (Table 4.1 and Table 4.2) and used in the response variable column for the corresponding trials designed using Statease 360 software. Statease 360 analyzes the data of particular attributes selected using ANOVA to detect significant differences in the response variables. A p-value < 0.05 indicates that there is a significant difference between the samples for the particular response variable which is essential for predicting the best formula.

Statease 360 analyzes the selected response variables to identify multiple optimal formulas. The desirability value, which ranges from 0 to 1, indicates the proximity of a formula to its optimum state. A desirability value closer to 1 facilitates the attainment of the best formula based on the response variable. This aids in selecting the most efficient formula for the given scenario for each segment.

Table 4.1 Health-conscious segment consumer liking of lucuma ice creams (n=53)

Prototype Label	Appearance Liking	Overall Aroma Liking	Overall Liking	Flavor Liking	Fruit Flavor Liking	Sweetness Liking	Overall Texture Liking	Mouthfeel Liking	Aftertaste Liking
LIC1-L	7.1 a	5.7 a	7.5 a	7.4 a	6.5 a	7.2 a	8.0 a	7.9 a	7.1 a
LIC2-L	6.7 ab	5.7 a	7.4 a	7.4 a	6.3 ab	7.1 ab	7.8 a	7.6 a	6.8 a
LIC3-L	6.9 a	5.8 a	6.4 bc	6.2 bc	5.6 c	6.2 cd	6.4 bc	6.5 bc	6.0 b
LIC4-L	6.6 abc	5.7 a	7.4 a	7.4 a	6.5 a	7.2 a	7.6 a	7.5 a	6.9 a
LIC5-L	6.5 abc	5.8 a	6.7 b	6.6 b	5.9 abc	6.8 ab	6.7 b	6.8 b	5.9 b
LIC6-M	6.5 abc	5.9 a	5.9 c	6.2 bc	5.8 bc	6.5 bc	6.1 bc	6.1 cd	5.5 bc
LIC7-M	6.6 abc	5.6 a	5.7 cd	5.8 c	5.4 cd	5.9 cde	5.9 c	5.8 d	5.1 cd
LIC8-M	6.0 cd	5.5 a	5.8 c	5.8 c	5.5 c	5.9 de	6.2 bc	6.0 cd	5.4 bcd
LIC9-H	6.1 bcd	5.7 a	5.0 de	4.9 d	4.8 de	5.5 ef	5.2 d	5.0 e	4.7 de
LIC10-H	5.6 d	5.5 a	4.2 f	4.4 d	4.4 e	5.2 f	4.2 e	4.2 f	4.4 e
LIC11-H	6.1 bcd	5.8 a	4.7 ef	4.7 d	4.7 e	5.3 ef	4.6 de	4.5 ef	4.7 de
Pr > F(Model)	<0.0001	0.934	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Table 4.2 Indulgent segment consumer liking of lucuma ice creams (n=51)

Prototype Label	Appearance Liking	Overall Aroma Liking	Overall Liking	Flavor Liking	Fruit Flavor Liking	Sweetness Liking	Overall Texture Liking	Mouthfeel Liking	Aftertaste Liking
LIC1-L	6.8 a	5.8 a	6.7 ab	6.7 ab	5.9 ab	6.8 a	7.4 a	7.4 a	6.5 a
LIC2-L	6.5 ab	5.7 ab	6.6 ab	6.7 ab	5.9 ab	6.8 a	7.3 a	7.0 a	6.4 a
LIC3-L	6.5 ab	5.5 abc	5.7 cd	5.8 cd	5.5 bc	5.6 bc	5.9 bcd	5.8 bc	5.5 b
LIC4-L	6.1 bcd	5.6 abc	7.0 a	7.2 a	6.3 a	7.0 a	7.5 a	7.3 a	6.9 a
LIC5-L	6.3 abc	5.7 ab	6.2 bc	6.1 bc	5.5 bc	6.0 b	6.5 b	6.3 b	5.5 b
LIC6-M	5.4 efg	5.4 abc	5.2 de	5.3 de	5.0 cd	5.5 bc	5.5 d	5.4 c	4.8 c
LIC7-M	5.7 cdef	5.4 abc	5.3 de	5.2 de	5.2 c	5.6 bc	5.6 cd	5.4 c	4.9 bc
LIC8-M	6.0 bcde	5.6 abc	5.5 d	5.5 cd	5.6 bc	6.0 b	6.2 bc	6.1 b	5.3 bc
LIC9-H	5.6 defg	5.2 bc	4.6 e	4.7 e	4.5 de	5.1 cd	4.5 e	4.5 d	4.1 d
LIC10-H	5.1 g	5.1 c	3.9 f	3.9 f	4.1 e	4.8 d	4.0 e	3.9 d	3.6 d
LIC11-H	5.2 fg	5.2 bc	3.8 f	4.0 f	4.1 e	4.6 d	4.3 e	4.0 d	3.7 d
Pr > F(Model)	<0.0001	0.125	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Results and Discussions

Overall Likability

The overall likeability attribute was analyzed and the summary statistics for health-conscious and indulgent segments are presented in Table 4.1 and Table 4.2. The analysis of variance (ANOVA) indicates that the p-value of the F-Test in the linear model is <0.0001 for both segments, meaning that the overall likeability attribute across the 11 formulations is significantly different.

The regression analysis (Table 4.1 and Table 4.2) reveals an R^2 value of 0.9601 for health-conscious segment and 0.9735 for indulgent segment, suggesting that the independent variables lucuma fruit powder, milk fat, and sucrose collectively account for 96.01% and 97.35% of the variation in overall likeability, respectively. The high R^2 values in the predicted equation for various attributes demonstrate the accuracy of the fitting.

Table 4.3 Statistical summary of overall liking for health-conscious segment

Analyzed components	Result
Mean	6.08
Standard Deviation	0.2668
Model	Linear Mixture
Sequential p-value	<0.0001
R-Square (R^2)	0.9601
Adjusted R^2	0.9430
Predicted R^2	0.8762
Mathematical Model Equations	6.40*Fat + 8.17*Sucrose + 0.99*Lucuma + 6.98*Base

Table 4.4 Statistical summary of overall liking for indulgent segment

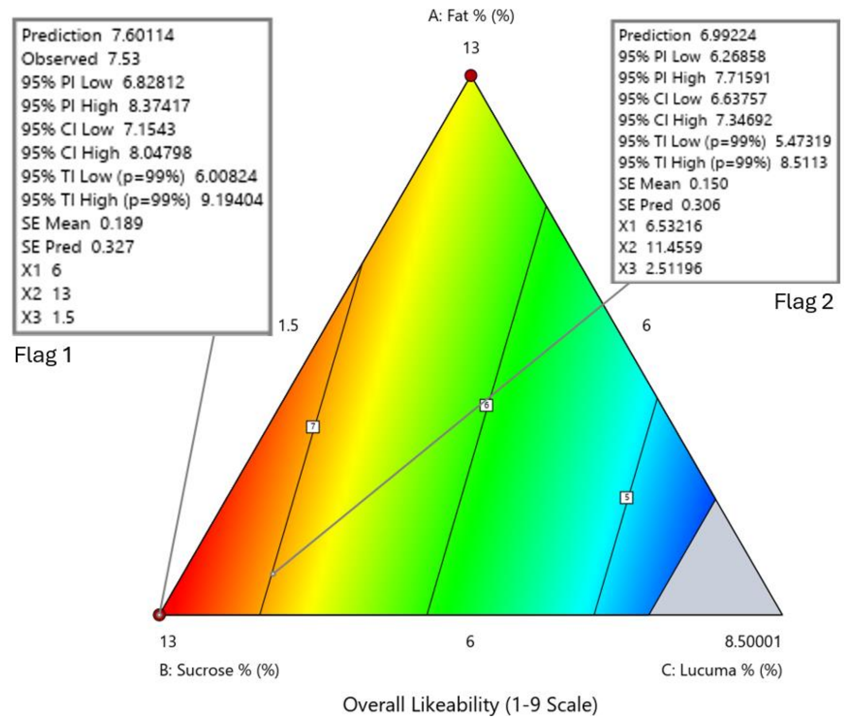
Analyzed components	**Result**
Mean	5.51
Standard Deviation	0.2155
Model	Linear Mixture
Sequential p-value	<0.0001
R-Square (R^2)	0.9735
Adjusted R^2	0.9621
Predicted R^2	0.8928
Mathematical Model Equations	5.77*Fat + 7.90*Sucrose + 0.65*Lucuma + 6.18*Base

Figure 4.1 and Figure 4.2 illustrate the distribution of overall likeability for health-conscious and indulgent segments, the formulas with the highest overall liking scores are depicted in the red area, followed by orange, yellow, green, and progressing to light to dark blue, indicating varying levels of overall liking responses.

Based on the contour plots of each segment (Figure 4.1 and Figure 4.2) and the mathematical model of overall liking using the linear model, it can be observed that the area on the graph of each segment is linearly distributed indicating that there is no interaction between the independent variables.

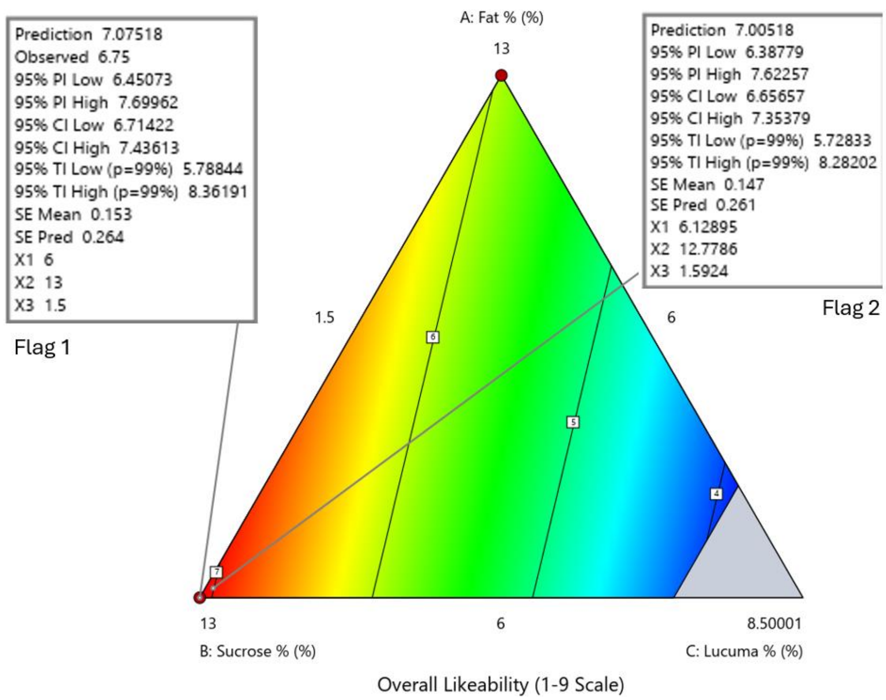
The comparison of contour plots for the two segments show that health-conscious consumers (Flag 1 of Figure 4.1) had a higher liking for the lucuma ice cream with an overall liking score of 7.6 as compared to indulgent consumers (Flag 1 of Figure 4.2) who had an overall likeability score of 7.1. One of the optimized formulations (Flag 2 of Figure 4.1 and Flag 2 of Figure 4.2) for lucuma ice cream with an overall liking score of 7.0 varies for health-conscious and indulgent consumers. For health-conscious consumers, the ingredients include lucuma fruit powder at 2.5%, fat at 6.5%, and sucrose at 11.5%. Whereas, for indulgent consumers, the proportion changes to lucuma fruit powder at 1.5%, fat at 6.1%, and sucrose at 12.8%. These results reveal that health-conscious consumers accepted higher levels of lucuma fruit powder and lower levels of sucrose compared to indulgent consumers.

Figure 4.1 Contour plot graph of overall likeability for health-conscious segment



Note: X1-Fat, X2-Sucrose, X3-Lucuma powder (% Wt./Wt.).

Figure 4.2 Contour plot graph of overall likeability for indulgent segment



Note: X1-Fat, X2-Sucrose, X3-Lucuma powder (% Wt./Wt.).

Overall Texture Liking

The overall texture liking attribute was analyzed and the summary statistics for health-conscious and indulgent segments are presented in Table 4.3 and Table 4.4. The analysis of variance (ANOVA) indicates that the p-value of the F-Test in the linear model is <0.0001 for both segments, meaning that the overall texture liking attribute across the 11 formulations is significantly different.

The regression analysis (Table 4.3 and Table 4.4) reveals an R^2 value of 0.9575 for health-conscious segment and 0.9526 for indulgent segment, suggesting that the independent variables lucuma fruit powder, milk fat, and sucrose collectively account for 95.75% and 95.26% of the variation in overall texture liking, respectively. The high R^2 values in the predicted equation for various attributes demonstrate the accuracy of the fitting.

Table 4.5 Statistical summary of overall texture liking for health-conscious segment

Analyzed components	**Result**
Mean	6.23
Standard Deviation	0.3063
Model	Linear Mixture
Sequential p-value	<0.0001
R-Square (R^2)	0.9575
Adjusted R^2	0.9393
Predicted R^2	0.8596
Mathematical Model Equations	6.33*Fat + 8.84*Sucrose + 0.84*Lucuma + 7.18*Base

Figure 4.3 and Figure 4.4 illustrate the distribution of overall texture liking for the health-conscious and indulgent segments. Similarly, as with overall liking, the formulas with the highest overall texture liking scores are depicted in the red area, followed by orange, yellow, green, and progressing to light to dark blue, indicating varying levels of overall texture liking response.

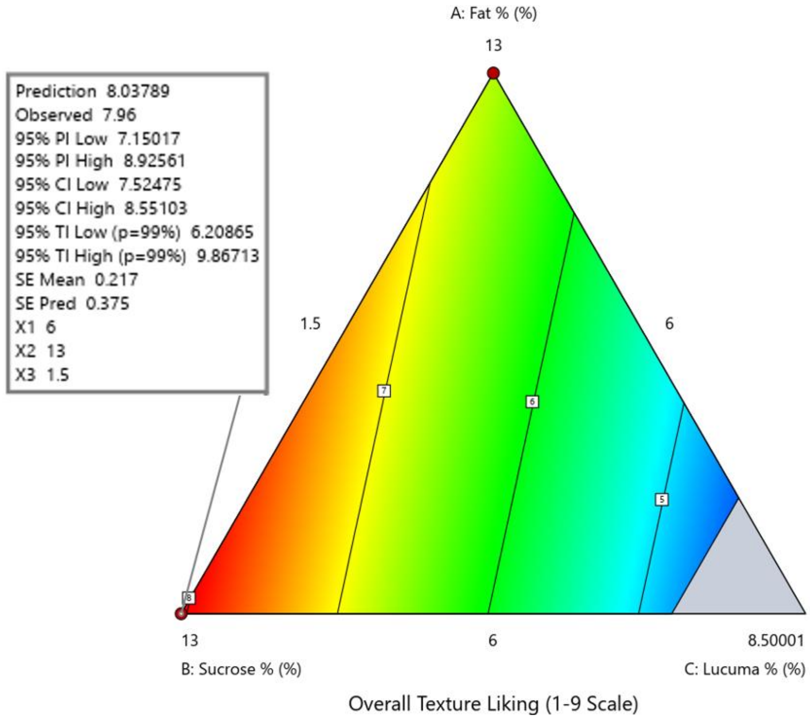
Table 4.6 Statistical summary of overall texture liking for indulgent segment

Analyzed components	**Result**
Mean	5.89
Standard Deviation	0.3230
Model	Linear Mixture
Sequential p-value	<0.0001
R-Square (R^2)	0.9526
Adjusted R^2	0.9323
Predicted R^2	0.8379
Mathematical Model Equations	6.07*Fat + 8.77* Sucrose + 0.69*Lucuma + 6.47*Base

Based on the contour plots of each segment (Figure 4.3 and Figure 4.4) and the mathematical model of overall texture liking using a linear model, it can be observed that the area on the graph of each segment is linearly distributed indicating that there is no interaction between the independent variables.

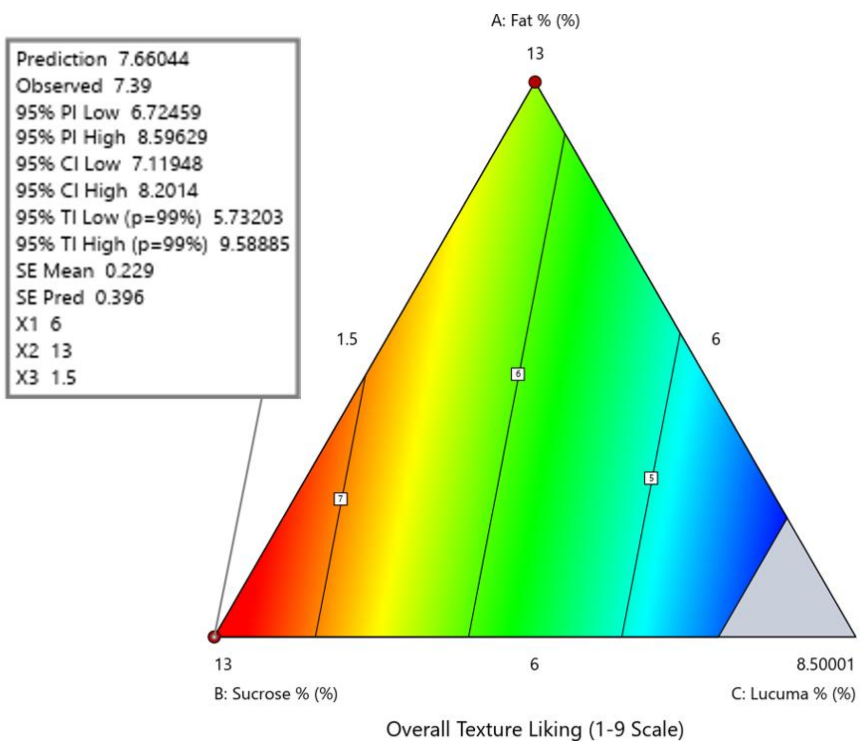
The study indicates that the health-conscious segment has a higher texture liking score of 8.0, compared to the indulgent segment with a score of 7.7 for the optimized formulation. This suggests that both segments perceive the texture of lucuma ice cream differently. Health-conscious consumers may be more tolerant to textural changes (grainy and powdery) with increased lucuma fruit powder levels in the ice cream, possibly due to their positive perception of lucuma fruit powder as a healthy ingredient.

Figure 4.3 Contour plot graph of overall texture liking for health-conscious segment



Note: X1-Fat, X2-Sucrose, X3-Lucuma powder (% Wt./Wt.).

Figure 4.4 Contour plot graph of overall texture liking for indulgent segment



Note: X1-Fat, X2-Sucrose, X3-Lucuma powder (% Wt./Wt.).

Mouthfeel Liking

The mouthfeel liking attribute was analyzed and the summary statistics for health-conscious and indulgent segments are presented in Table 4.5 and Table 4.6. The analysis of variance (ANOVA) indicates that the p-value of the F-Test in the linear model is <0.0001 for both segments, signifying that the mouthfeel liking attribute across the 11 formulations is significantly different.

The regression analysis (Table 4.5 and Table 4.6) reveals an R^2 value of 0.9697 for the health-conscious segment and 0.9712 for the indulgent segment, suggesting that the independent variables lucuma fruit powder, milk fat, and sucrose collectively account for 96.97% and 97.12% of the variation in mouthfeel liking, respectively. The high R^2 values in the predicted equation for various attributes demonstrate the accuracy of the fitting.

Table 4.7 Statistical summary of mouthfeel liking for health-conscious segment

Analyzed components	Result
Mean	6.18
Standard Deviation	0.2629
Model	Linear Mixture
Sequential p-value	<0.0001
R-Square (R^2)	0.9697
Adjusted R^2	0.9566
Predicted R^2	0.9018
Mathematical Model Equations	6.44*Fat + 8.68*Sucrose + 0.50*Lucuma + 7.17*Base

Figure 4.5 and Figure 4.6 illustrate the distribution of mouthfeel liking for health-conscious and indulgent segments. The formulas with the highest mouthfeel liking scores are depicted in the red area, followed by orange, yellow, green, and progressing to light to dark blue, indicating varying levels of mouthfeel liking response.

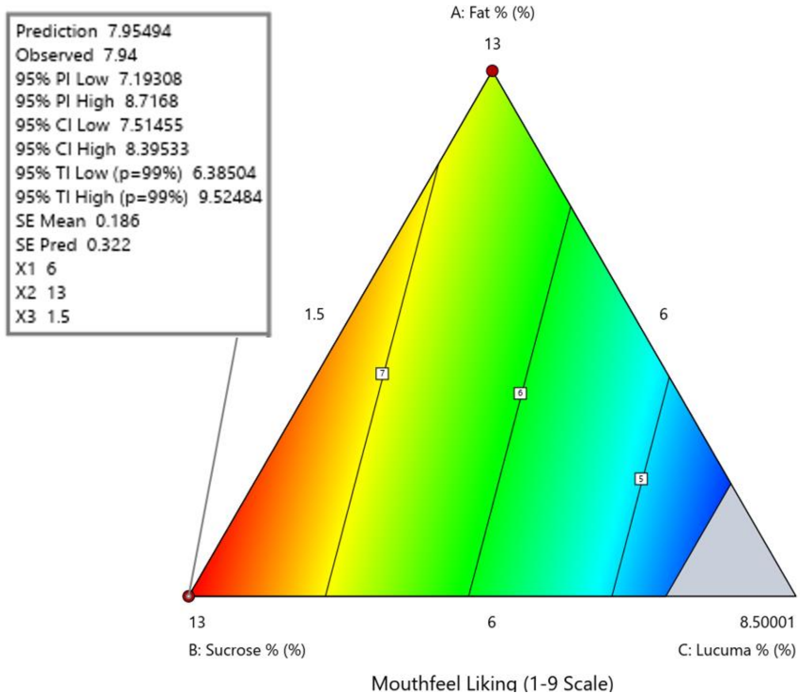
Table 4.8 Statistical summary of mouthfeel liking for indulgent segment

Analyzed components	Result
Mean	5.74
Standard Deviation	0.2543
Model	Linear Mixture
Sequential p-value	<0.0001
R-Square (R^2)	0.9712
Adjusted R^2	0.9589
Predicted R^2	0.9077
Mathematical Model Equations	5.81*Fat + 8.81*Sucrose + 0.5758*Lucuma + 6.28*Base

Based on the contour plots of each segment (Figure 4.5 and Figure 4.6) and the mathematical model of mouthfeel liking using a linear model, it can be observed that the area on the graph of each segment is linearly distributed indicating that there is no interaction between the independent variables.

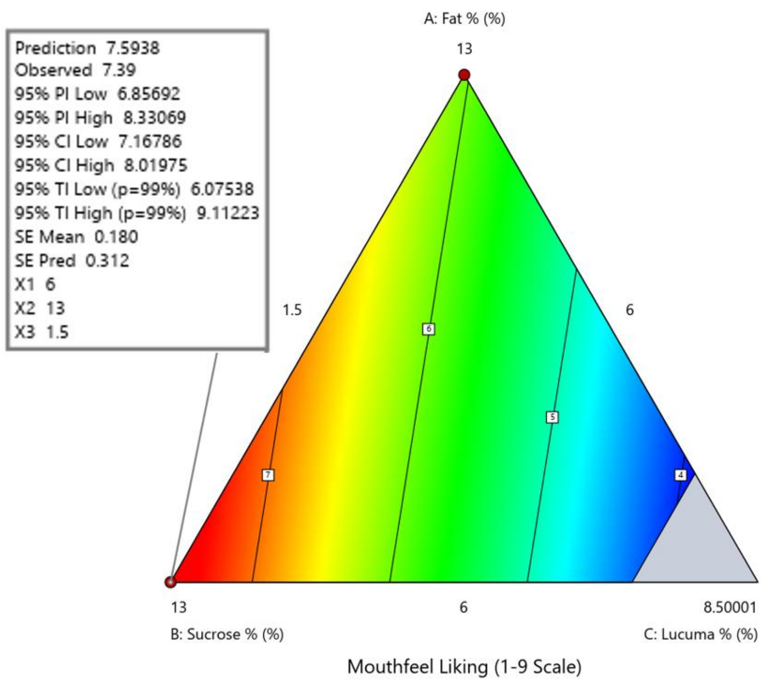
The health-conscious segment has a higher score of 8.0 for mouthfeel liking, compared to the indulgent segment with a score of 7.6 for the optimized formulation, showing a similar pattern of overall texture liking.

Figure 4.5 Contour plot graph of mouthfeel liking for health-conscious segment



Note: X1-Fat, X2-Sucrose, X3-Lucuma powder (% Wt./Wt.).

Figure 4.6 Contour plot graph of mouthfeel liking for indulgent segment



Note: X1-Fat, X2-Sucrose, X3-Lucuma powder (% Wt./Wt.).

Optimization DFA

The DFA was utilized for the simultaneous optimization of lucuma ice cream, where desirability values range from 0 to 1. A value of zero (0) signifies no desirability, while a value of 1 indicates the highest possible desirability within the set constraints. In this study, four crucial quality indicators were chosen for optimization, with constraints established accordingly. These constraints were determined based on their impact on the product, ensuring optimal quality. Therefore, desirable scores were selected to enhance product quality.

The outcomes, depicted in Figure 4.7 for the health-conscious segment, indicate that lucuma ice cream prepared by incorporating 1.5% lucuma fruit powder, 6% milk fat, and 13% sucrose with an overall liking score of 7.6, overall texture liking score of 8.0, and mouthfeel liking score of 8.0, will result in a desirability score of 1.Figure 4.8 for the indulgent segment, indicates that lucuma ice cream prepared by incorporating 1.5% lucuma fruit powder, 6% milk fat, and 13% sucrose with an overall liking score of 7.0, overall texture liking score of 7.7, and mouthfeel liking score of 7.6, result in a desirability score of 1. The lucuma ice cream produced using optimization techniques was well-received, showcasing high acceptability.

Figure 4.7 Desirability function analysis for health-conscious segment

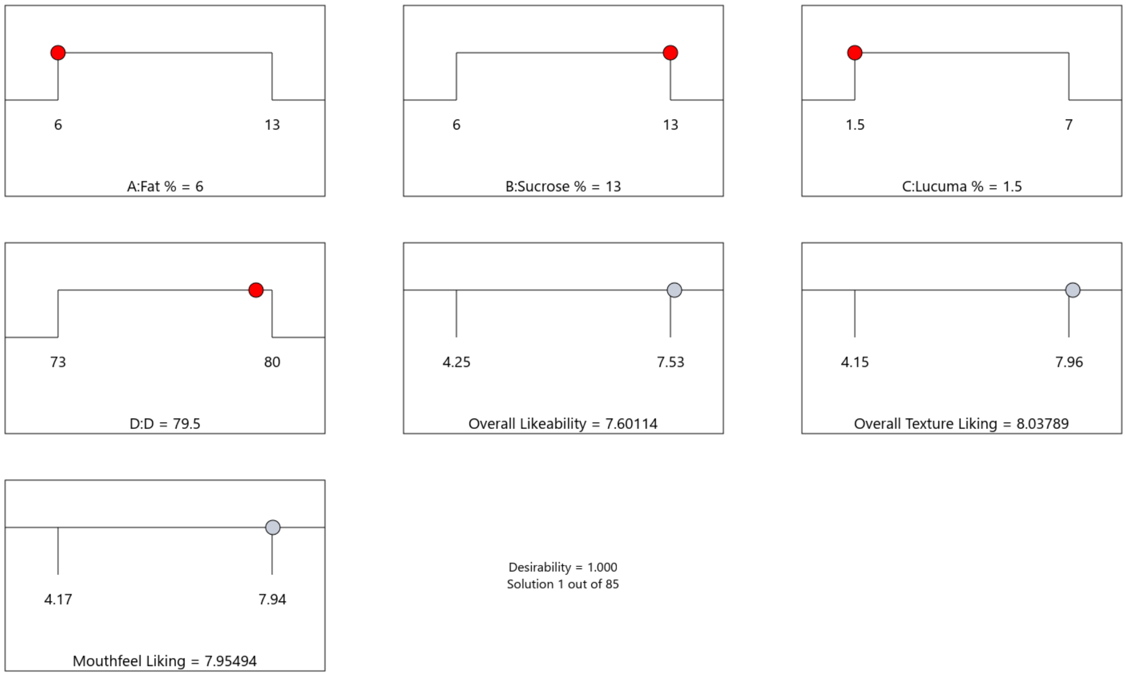
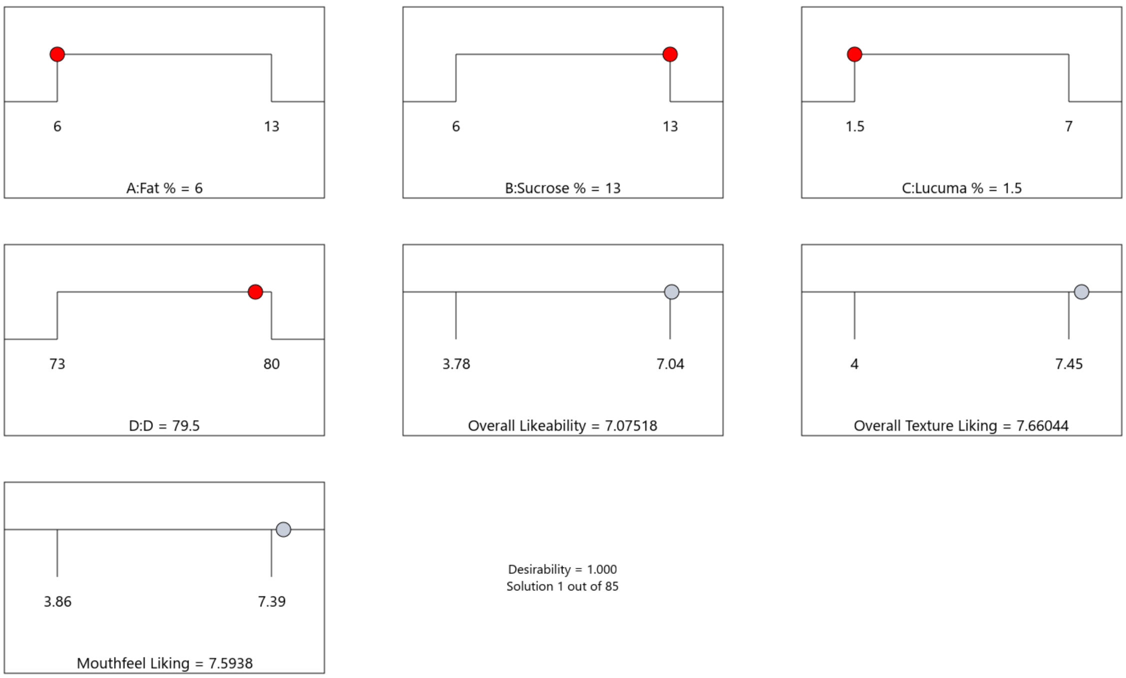


Figure 4.8 Desirability function analysis for indulgent segment



Conclusion

Health-oriented consumers had an optimized score of 7.6 on a 9-point hedonic scale, while indulgent consumers scored 7.1 for the same formulation containing 1.5% lucuma fruit powder, 13% sucrose, and 6.0% fat, indicating a difference in their liking patterns. The results show that health-conscious consumers perceived the prototypes as sweeter than indulgent consumers. This suggests that ice cream targeting the health-consumer market could be formulated with less sweetness (added sugar), maintaining taste while offering a healthier profile. The research also indicates that health-oriented consumers are more accepting of higher lucuma levels in ice cream formulations compared to the indulgent consumer segment. The overall liking scores for the lucuma ice cream prototypes with high and low-fat content showed no significant difference for both health-conscious and indulgent consumer segments, indicating that incorporating lucuma fruit powder can help reduce fat in ice creams without impacting consumer satisfaction. The evaluated prototypes offer healthier alternatives without affecting consumer acceptance.

Applications

The study highlights the potential of novel ingredients in the U.S. market like lucuma, demonstrating its ability to enhance nutritional profiles without compromising sensory qualities. Leveraging the positive findings on lucuma fruit acceptability, a broader product line can be developed. This may include variations in fat content, flavors, formats (e.g., bars, novelties), or even incorporating lucuma into other dairy or non-dairy frozen desserts.

This research also provides a practical framework for developing new food products, emphasizing consumer-centricity and efficient optimization. By segmenting consumers based on psychographic data and analyzing their sensory responses, food manufacturers and researchers can develop innovative products that precisely cater to specific needs and preferences. This approach minimizes costly trial-and-error, leading to faster and more cost-effective product development.

References

Bae, H C., Chae, M., & Ryu, K. (2010, January 1). Consumer behaviors towards ready-to-eat foods based on food-related lifestyles in Korea. , 4(4), 332-332. https://doi.org/https://doi.org/10.4162/nrp.2010.4.4.332

Ice Cream Market in the United States: Market Snapshot to 2020. (2017, February 1). https://www.proquest.com/reports/ice-cream-market-united-states-snapshot-2020/docview/1872816196/se-2

Kwak, H S., Meullenet, J., & Lee, Y. (2016, April 18). Sensory profile, consumer acceptance and driving sensory attributes for commercial vanilla ice creams marketed in the United States. Wiley-Blackwell, 69(3), 346-355. https://doi.org/https://doi.org/10.1111/1471-0307.12314

ROININEN, K., LÄHTEENMÄKI, L., & TUORILA, H. (1999, January 22). Quantification of Consumer Attitudes to Health and Hedonic Characteristics of Foods, Appetite,. Appetite, 33(1), 71-88. https://doi.org/https://doi.org/10.1006/appe.1999.0232

Saba, A., Sinesio, F., Moneta, E., Dinnella, C., Laureati, M., Torri, L., Peparaio, M., Civitelli, E S., Endrizzi, I., Gasperi, F., Bendini, A., Toschi, T G., Predieri, S., Abbà, S., Bailetti, L., Proserpio, C., & Spinelli, S. (2019, April 1). Measuring consumers attitudes towards health and taste and their association with food-related life-styles and preferences. Elsevier BV, 73, 25-37. https://doi.org/https://doi.org/10.1016/j.foodqual.2018.11.017

Singh, G. (2022, February 8). Sensory and consumer evaluation of lucuma powder as an ingredient for ice cream in the United States

Appendix A - Screener and Questionnaire Used in Consumer Study

Screener

SQ 1. What is your gender?

Male

Female

SQ. 2 Are you currently pregnant or nursing?

Yes

No

SQ.3 Are YOU allergic or sensitive to ANY of the following foods? (check al that apply)

Wheat (gluten)

Soybean

Egg

Milk

Fish

Crustacean shellfish

Sesame

Tree Nut

Peanut

Other (specify)

I am not allergic to any of the

above

SQ.4 Are you currently scheduled to participate in a market research study or taste test?

Yes

No

SQ.5 When was the last time you, yourself, participated in a market research study or taste test?

In the past month

In the past 2 months

In the past 3 months

In the past 4-6 months

6 months or more ago

I have never participated in a consumer research or marketing research study about a food or beverage

SQ. 6 Are you currently experiencing any cold, Covid or flu-like symptoms?

Yes

No

SQ. 7 Which of the following includes your current age?

17 years or younger

18-34 years old

35-50 years old

51-65 years old

66 years or older

SQ. 8 With which of the following ethnicities do you most closely identify?

African American/Black

Hispanic/Latino

Asian

Pacific Islander

American Indian/Native

American

Caucasian/White

Other (please specify)

Prefer not to answer

SQ. 9 What is the last level of education that you completed?

Below high school

High School

Some College but no degree/Technical school

College degree (bachelors)

Masters degree

Doctorate degree

Professional degree (JD,MD)

SQ. 10 Which number range best describes your total annual household income before taxes?

Under $25,000

$25,000 to $49,999

$50,000 to $74,999

$75,000 to $99,999

$100,000 to $124,999

$125,000 to $149,999

$150,000 to $199,999

$200,000 or more

SQ. 11 Who makes up your current household?

Myself

Myself and my spouse/partner

Myself and my kids under 18 years old

Myself and my adult children

Myself, my spouse/partner, and my kids under 18 years old

Myself, my spouse/partner, and my adult kids

SQ. 12 What age groups do your children fall into that are living at home with you? (check all that apply)

0 - 11 months old

1 - 5 years old

6 - 10 years old

11 - 13 years old

14 - 18 years old

SQ. 13 How much of the food shopping do you, yourself, do for your household?

All of the food shopping (100%)

Most of the food shopping (50-99%)

Some of the food shopping (25-49%)

Very little of the food shopping (1-24%)

None of the food shopping (0%)

SQ. 14 Which, if any, of the following desserts do you like to consume(check all that apply)

Ice Cream/Frozen desserts

Cookies

Cake

Brownies

Pie

None of the above

SQ. 15 You mentioned you liked to eat ice cream/frozen desserts, which of the following types of ice cream or frozen desserts do you purchase and consume (check all that apply)

Super Premium or Premium Ice Cream-dairy (e.g., Ben & Jerry's, Graeters, Haagen Dazs, Tillamook, Talenti)

Regular Ice Cream/ Frozen Desserts-dairy & nondairy (e.g., Blue Bunny, Breyer's, Belfonte, Blue Bell, Store brands - Costco, Walmart)

Light or Reduced-Sugar/Fat Ice Cream-dairy (Halo Top, Ben and Jerry's Lights, Breyers Smart Carb, Artic Zero, Enlightened)

High-Protein Ice Cream or Frozen Desserts (e.g,Fairlife, Halo Top, Enlightened Light, Skinny Cow, Yasso, Keto Pint)

Plant based Frozen Desserts - Made with almond/coconut/cashew milk, etc (e.g., So Delicious, Oatly, Van Leeuwen, Favorite Day, 365 Whole Foods Market)

None of the above

SQ. 16 Which one of the following types of ice cream or frozen desserts do you consume the most(select only one)

Super Premium or Premium Ice Cream-dairy (e.g., Ben & Jerry's, Graeters, Haagen Dazs, Tillamook, Talenti)

Regular Ice Cream/ Frozen Desserts-dairy & nondairy (e.g., Blue Bunny, Breyer's, Belfonte, Blue Bell, Store brands - Costco, Walmart)

Light or Reduced-Sugar/Fat Ice Cream-dairy (Halo Top, Ben and Jerry's Lights, Breyers Smart Carb, Artic Zero, Enlightened)

High-Protein Ice Cream or Frozen Desserts (e.g,Fairlife, Halo Top, Enlightened Light, Skinny Cow, Yasso, Keto Pint)

Plant based Frozen Desserts - Made with almond/coconut/cashew milk, etc (e.g., So Delicious, Oatly, Van Leeuwen, Favorite Day, 365 Whole Foods Market)

SQ. 17 You mentioned you liked to consume Super Premium and Regular ice creams and frozen desserts, how often do you consume them

Multiple times per week

Once a week

2 to 3 times a month

Once a month

Once every 2 to 3 months

Once every 4 to 6 months

Less than once a year

SQ. 18 You mentioned you liked to consume Light/Reduced Fat and/or Sugar/High-Protein/Plant-based ice creams and frozen desserts, how often do you consume them

Multiple times per week

Once a week

2 to 3 times a month

Once a month

Once every 2 to 3 months

Once every 4 to 6 months

Less than once a year

SQ. 19 You said you like to consume ice cream, which of the following flavors of ice cream do you like? (choose all that apply)

Vanilla

Chocolate

Strawberry

Cookies N' Cream

Chocolate Chip

Butter Pecan

French Vanilla

Chocolate Chip Cookie Dough

Caramel/Salted Caramel

None of the above

SQ. 20 How much do you agree or disagree with the following statement? "I enjoy trying new flavors of ice cream"

Strongly Disagree

Disagree

Somewhat Disagree

Neither Agree nor Disagree

Somewhat Agree

Agree

Strongly Agree

Questionnaire

Concept

Introducing lucuma Fruit Ice cream, made with fresh milk and cream, and ingredients from natural sources like Peruvian lucuma fruit. Lucuma fruit, also known as the "Gold of the Incas", is an exotic fruit native to Peru. The lucuma fruit powder is used as a natural sweetener and flavor in the ice cream replacing processed cane sugar. It is rich in nutrients and antioxidants which are good for your heart and immune system.

Q1: How much do you like or dislike the OVERALL APPEARANCE of this ice cream?

Dislike extremely – Like Extremely (9-point)

Q2: How would you describe the COLOR of this ice cream sample?

Much too light

Somewhat too light

Just about right

Somewhat too dark

Much too dark

Q3: How much do you like or dislike the OVERALL AROMA of this ice cream?

Dislike extremely – Like Extremely (9-point)

Q4: Considering the appearance, aroma, flavor, taste, and texture of this ice cream, how much do you like or dislike the sample OVERALL?

Dislike extremely – Like Extremely (9-point)

Q5: How much do you like or dislike the OVERALL FLAVOR of this ice cream sample?

Dislike extremely – Like Extremely (9-point)

Q6: Please touch the line scale below to rate the STRENGTH OF THE FRUIT FLAVOR of this ice cream.

Q7: How much do you like or dislike the FRUIT FLAVOR of this ice cream sample?

Dislike extremely – Like Extremely (9-point)

Q8: How much do you like or dislike the SWEETNESS of this ice cream sample?

Dislike extremely – Like Extremely (9-point)

Q9: Please touch the line scale below to rate the SWEETNESS INTENSITY of this ice cream.

Q10: Check all the FLAVORS that describe this ice cream. (choose all that apply)

Vanilla

Milky

Creamy

Buttery

Ripe fruit

Maple syrup

Caramel

Coffee

Butter Pecan

Nutty

Walnut

Chocolate

Butterscotch

French Vanilla

Chemical/Artificial

Overripe Fruit

Bitter

Other: (please specify)

Q 11: How much do you like or dislike the OVERALL TEXTURE of this ice cream?

Dislike extremely – Like Extremely (9-point)

Q 12: How much do you like or dislike the OVERALL MOUTHFEEL of this ice cream sample?

Dislike extremely – Like Extremely (9-point)

Q13: How much do you like or dislike the AFTERTASTE of this ice cream sample?

Dislike extremely – Like Extremely (9-point)

Q 14: Please rate how much you agree or disagree with the following statements.

Q 14.1: The healthiness of food has little impact on my food choice.

Strongly disagree – Agree (7-Point)

Q 14.2: I am very particular about the healthiness of food I eat.

Strongly disagree – Agree (7-Point)

Q 14.3: I eat what I like. I do not worry much about the healthiness of food.

Strongly disagree – Agree (7-Point)

Q 14.4: It is important for me that my diet is low in fat and added sugars.

Strongly disagree – Agree (7-Point)

Q 14.5: I always follow a healthy and balanced diet.

Strongly disagree – Agree (7-Point)

Q 14.6: It is important for me that my daily diet contains a lot of vitamins and minerals.

Strongly disagree – Agree (7-Point)

Q 14.7: The healthiness of snacks makes no difference to me.

Strongly disagree – Agree (7-Point)

Q 14.8: I do not avoid food even if they may raise my cholesterol and sugar levels.

Strongly disagree – Agree (7-Point)

Q 14.9: I do not think that light (reduced fat/sugar) products are healthier than conventional product.

Strongly disagree – Agree (7-Point)

Q 14.10: In my opinion, the use of light (reduced fat/sugar) products does not improve one's health.

Strongly disagree – Agree (7-Point)

Q 14.11: In my opinion, light (reduced fat/sugar) products don't help to drop cholesterol levels.

Strongly disagree – Agree (7-Point)

Q 14.12: I believe that eating light (reduced fat/sugar) products keeps one's cholesterol level under control.

Strongly disagree – Agree (7-Point)

Q 14.13: I believe that eating light (reduced fat/sugar) products keeps one's body in good shape.

Strongly disagree – Agree (7-Point)

Q 14.14: In my opinion by eating light (reduced fat/sugar) products one can eat more without getting too many calories.

Strongly disagree – Agree (7-Point)

Q 14.15: I try to eat food that do not contain additives.

Strongly disagree – Agree (7-Point)

Q 14.16: I do not care about additives in my daily diet.

Strongly disagree – Agree (7-Point)

Q 14.17: I do not eat processed foods, because I do not know what they contain.

Strongly disagree – Agree (7-Point)

Q 14.18: I would like to eat only organically grown vegetable.

Strongly disagree – Agree (7-Point)

Q 14.19: In my opinion, artificially flavoured are not harmful for my health.

Strongly disagree – Agree (7-Point)

Q 14.20: In my opinion, organically grown foods are no better for my health than those grown conventionally.

Strongly disagree – Agree (7-Point)

Q 14.21: In my opinion it is strange that some people have cravings for chocolate.

Strongly disagree – Agree (7-Point)

Q 14.22: In my opinion it is strange that some people have cravings for sweets.

Strongly disagree – Agree (7-Point)

Q 14.23: In my opinion it is strange that some people have cravings for ice-cream.

Strongly disagree – Agree (7-Point)

Q 14.24: I often have cravings for chocolate.

Strongly disagree – Agree (7-Point)

Q 14.25: I often have cravings for sweets .

Strongly disagree – Agree (7-Point)

Q 14.26: I often have cravings for ice-cream.

Strongly disagree – Agree (7-Point)

Q 14.27: I reward myself by buying something really tasty.

Strongly disagree – Agree (7-Point)

Q 14.28: I indulge myself by buying something really delicious.

Strongly disagree – Agree (7-Point)

Q 14.29: When I am feeling down I want to treat myself with something really delicious.

Strongly disagree – Agree (7-Point)

Q 14.30: I avoid rewarding myself with food.

Strongly disagree – Agree (7-Point)

Q 14.31: In my opinion, comforting oneself by eating is self deception.

Strongly disagree – Agree (7-Point)

Q 14.32: I try to avoid eating delicious food when I am feeling down.

Strongly disagree – Agree (7-Point)

Q 15: Please answer the following questions about yourself.

Q 15.1: What is your gender?

Male

Female

Q 15.2: Which of the following includes your current age?

17 years or younger

18-34 years old

35-50 years old

51-65 years old

66 years or older

Q 15.3: After tasting these ice cream samples, how interested would you be in buying Lucuma Ice Cream?

Definitely will not buy

Probably will not buy

Might or might not buy

Probably will buy

Definitely will buy