AI-based online review analysis versus consumer check-all-that apply (CATA) for drivers of liking in plant-based meat alternatives

by

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Abstract

Plant-based meat alternatives (PBMAs) have gained attention as sustainable alternatives to animal-based products; however, their sensory quality remains a major barrier to consumer acceptance. Conventional sensory testing provides controlled and reliable data but can be time-consuming and resource intensive. AI-assisted analysis of online reviews may offer a rapid, complementary approach by extracting sensory information from consumers' real-world product experiences. This study compared conventional consumer testing with AI-assisted online review analysis to identify drivers of liking for plant-based chicken products. In a controlled consumer study, 100 participants evaluated six plant-based chicken products using hedonic scales and Check-All-That-Apply (CATA) questions, followed by ANOVA, penalty-lift analysis, and Partial Least Squares Regression (PLSR). Attributes identified as drivers of liking across the penalty-lift and PLSR analyses included "meaty/savory," "chicken-like," "spice/herb," "toasted/brown," "crispy," "tender," "crunchy," and "moist/juicy," while "cardboard" was associated with disliking. For the AI-based approach, ChatGPT analyzed 631 Amazon reviews collected using Octoparse. After cleaning, 182 sensory-relevant reviews were retained. Qualitative analysis of review text identified positive drivers such as "juicy," "moist," "crispy," "crunchy," "soft," "firm," "savory," "salty" and "seasoned," while negative drivers included "dry," "chewy," "rubbery," "tough," "greasy," "oily," "bland," and "spongy." Quantitative analysis of attribute mentions and star ratings using PLSR showed that "crunchy," "juicy," "crispy," and "fishy" were positively associated with higher star ratings, whereas "rubbery," "tough," and "salty" were negative predictors. In addition, based on product ingredients, AI inferred desirable attributes such as "fibrous," "juicy," "savory," "brothy," "toasted," "allium/onion," "moist," and "cohesive" as potential drivers of liking, and undesirable attributes

such as “rubbery,” “gummy,” “crumbly,” “chalky,” “pasty,” “dry,” “beany,” “green,” “artificial,” and “flat” as potential drivers of disliking. The controlled consumer test identified more attributes that significantly differentiated the products, (24 of 32) using Cochran’s Q test, compared with six of 12 attributes identified from the quantitative AI analysis of online reviews using Pearson’s chi-square test. Nevertheless, the methods aligned for several discriminating descriptors, including “chicken-like,” “chewy,” “crispy,” and “crunchy.” Multiple Factor Analysis further demonstrated substantial agreement between datasets, with an RV coefficient of 0.781. Comparison of the identified drivers of liking and disliking between the consumer study and quantitative AI approach showed that “juicy” and “crispy” were consistently associated with higher liking scores and star ratings, respectively, while “tough” was associated with lower liking scores and star ratings. In contrast, “fishy” was positively associated with star ratings in the online review analysis but negatively associated with liking in the consumer study. This discrepancy highlights a limitation of online review analysis, including potential ambiguity in the meaning of sensory terms across consumers and testing contexts. Sensory descriptors do not always indicate whether an attribute was perceived positively or negatively, and star ratings may reflect the overall product experience rather than the effect of an individual attribute. Overall, AI-assisted analysis of online reviews captured sensory patterns comparable to controlled consumer testing and may provide a rapid complementary tool for PBMA product development. However, because online reviews are uncontrolled and vary in sensory detail, AI-generated findings should be interpreted alongside findings obtained using conventional sensory methods before product optimization.

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Chapter 1 - Literature review

Plant-based Meat Alternatives

For centuries, traditional plant-based proteins such as tofu and tempeh, among others, have existed and formed a significant part of meal options for consumers, especially in Asia; however, these products were not intended to mimic the sensory experiences elicited by consuming meat (Zhao et al., 2023). Recent research in the food industry has focused on two varieties of meat analogs: cultured meat (meat produced for consumption using animal cells, based on the growth and repair mechanisms of animal muscle tissue (Post, 2014; Hocquette, 2016)) and plant-based meat.

Plant-based meat alternatives or analogs (PBMA) are products designed to possess similar characteristics to animal products; thus, they exhibit similar functional properties to the animal product they aim to mimic, despite having a different composition (Singh & Sit, 2022; Joshi & Kumar, 2015). Protein sources for these products typically come from legumes and cereals, and soy proteins and gluten are widely used in PBMAs because of their economic viability (Wild et al., 2014; Joshi & Kumar, 2015). Ultimately, PBMAs are formulated by combining these protein sources with secondary ingredients such as vegetable oils, herbs and spices, and quality enhancers (Jung et al., 2024).

Owing to their distinctive ability to mimic meat, PBMAs are expected to appeal to an extensive consumer base, including vegetarians, but are not restricted to these consumers. They may also appeal to flexitarians and traditional meat-eaters who are either looking to reduce their meat intake due to health or ethical reasons, or who simply want to explore more protein options in their diets (Szejda & Wilks, 2020; Joshi & Kumar, 2015). The increasing market for PBMAs has led to more product development efforts by manufacturers willing to invest in this area,

resulting in an expanded supply of PBMAs and a wide range of forms to match their existing meat counterparts.

Categories

Several techniques can be used to create meat-like textures in PBMAs, which are heavily dependent on the type of meat product being mimicked. Meat products are primarily classified into ground, comminuted, and whole-muscle products. Likewise, PBMAs can be classified according to the type of meat product they are intended to mimic (Dekkers et al., 2018). They include burgers, meatballs, minced products, pieces, chicken cutlets, chicken nuggets, cold cuts, sausages, and seafood (Romão, 2023; Bryngelsson et al., 2022). Ishaq et al. (2022) categorized plant-based meat products into three groups: coarse ground (burgers and nuggets), emulsified (deli slices and hot dogs), and loose (taco or chili meat). Similarly, Kyriakopoulou et al. (2021) described the production process of three groups of PBMAs: emulsion-type products (e.g., sausages, frankfurters, bologna, mortadella); burgers, patties, and nuggets, which are comminuted products designed to recreate the bite, chewiness, succulence, and firmness of animal-based ground meat; and chicken-like and steak-like products, which aim to mimic whole-cut meats (e.g., chicken, pork, and beef) characterized by long fibers or layered structures.

As reviewed by Andreani et al. (2023), burgers are the most widely explored PBMA category in consumer research. This is largely attributed to the popularity of traditional animal-based burgers, driven by their nutritional composition, availability, convenience, affordability, and sensory appeal. Examples of companies producing PBMAs in the U.S. market include Impossible Foods, Beyond Meat, Gardein, Lightlife, MorningStar Farms, Dr. Praeger's, and Hampton Creeks. Impossible Foods created its burger product by using heme derived from soy leghemoglobin to impart a red color and enhance juiciness. In contrast, Beyond Meat achieves

juiciness primarily with coconut and olive oils, while beet extracts contribute to the red color, and ingredients such as yeast and fiber are used to help replicate the flavor and texture of meat (Jung et al., 2024).

Ingredients Technology

The quality indices of meat alternatives, such as consistency, flavor, and appearance, among others, are heavily reliant on ingredient selection, with meat alternatives being mostly composed of 50-80% water, 4-20% non-textured protein, 10-25% textured vegetable proteins, 3-10% flavor enhancing additives, 0-15% fats, 0-5% coloring agents, and 1-15% binding agents (Ahmad et al., 2022). The combination of these ingredients provides PBMAs with the expected sensory properties (texture, flavor), making it possible for them to evoke sensory experiences like those of the animal-based products they are intended to mimic when consumed.

Water

Water is a key component, with the highest proportion in PBMA formulations due to its function as a hydration medium for the different dried ingredients, as well as a plasticizer and foaming agent during processing (Kyriakopoulou et al., 2021). For instance, water aids in the extrusion of plant proteins by influencing the viscosity of the melt, participating in chemical reactions, and affecting extrusion temperature and pressure (Zhang et al., 2019). Additionally, the ability of proteins to interact with water affects some of their important functional properties, such as solubility, swelling, gelation, and emulsion stabilization (Peters et al., 2017). Water must be available and in appropriate quantities for these functionalities to occur properly. It is also worth noting that higher water content may increase juiciness in PBMAs, which is an important sensory attribute for consumer acceptance of meat products and is therefore also an important characteristic of meat analogues.

Proteins

Proteins are a group of macronutrients critical for the proper functioning of the human body due to their role in building muscles and tissues, among other functions (Benkovic et al., 2023). Proteins, specifically those from plant sources, form the second largest component of PBMAs after water, as indicated in the ingredient lists of PBMAs. They are an important component due to their functional properties, which include water and oil retention, solubility, emulsification, gelation, and foaming, all of which are essential for creating a desirable PBMA structure (Ahmad et al., 2022). The development of PBMAs began with the production of dry texturized vegetable proteins (TVP), produced through extrusion cooking of defatted soy meal, soy protein concentrates, or wheat gluten (Wild et al., 2014; Zahari et al., 2022; Joshi & Kumar, 2015). Texturization is a process through which proteins can be converted into fibrous structures resembling meat using food processing techniques such as extrusion cooking, electrospinning, freezing, shear cell, or Couette cell technology (Boukid, 2021, as cited in Ozturk & Hamaker, 2023; Dekkers et al., 2018). TVP is commonly derived from a range of leguminous crops, including soybeans, clover, alfalfa, peas, lupine, and faba beans, and is used to create PBMA textures that mimic those of animal proteins (Singh et al., 2021). Among these, soy is the dominant and most used protein source for the production of PBMAs, due to its traditional use in tofu and tempeh for centuries in Asia (He et al., 2020; Singh & Sit, 2022)

Soy Protein

Soybeans are a high-quality, nutrient-dense legume, rich in fat, fiber, protein, micronutrients, and vitamins (Singh et al., 2021). Notably, soy protein is considered a complete protein because it contains all nine essential amino acids required by the human body. Depending on the cultivar and climatic conditions, soybeans may contain approximately 35-40%

protein, 20% lipids, 9% dietary fiber, and 8.5% moisture based on the dry weight of mature raw seeds (Sheneni & Momoh, 2023). Proteins from soybeans, known as soy proteins, are extremely versatile and possess the ability to create the meat-like texture desired in PBMAs, and are available at relatively low cost (Ahmad et al., 2022; Zhang et al., 2021), hence their widespread use in PBMAs. However, scientific research and the PBMA market are gradually shifting toward the use of raw materials other than soy due to growing concern related to GMOs, allergies, and unfavorable climatic conditions for soy cultivation, among other factors (Andreani et al. 2023). Soy proteins are utilized in PBMA formulations in various forms, such as soy flour, soy protein isolates, or soy protein concentrates (Ahmad et al., 2022). In these forms, soy proteins are either used directly or can undergo texturization to produce ingredients that contribute to improved mouthfeel, chewiness, and hardness in the finished plant-based product (Benkovic et al., 2023; Chiang et al., 2018, as cited in Singh et al., 2021). To produce PBMAs, a blend of textured and non-textured soy proteins may be used (Malav et al., 2015, as cited in Singh et al., 2021). Notably, among different combinations of vegetable proteins, soy protein isolate has been reported to significantly affect overall preference, with higher inclusion levels associated with greater preference (Ahmad et al., 2022).

Pea Protein

Pea is another nutritionally rich legume whose seeds contain a good mix of both macronutrients and micronutrients. Peas contain approximately 17-22 g of carbohydrates, 20-50 g of starch, 14-26 g of dietary fiber, 6.2-6.5 g of protein, 0.4 g of fat, and 1.0 g of ash per 100 g; additionally, peas provide essential minerals (9-10 mg of calcium, 3-5 mg of sodium, and 97-99 mg of potassium per 100 g) and are also a source of B vitamins (approximately 0.7 mg of riboflavin, 5-6 mg of thiamine, and 0.54 mg of folate per kilogram) (Kumari & Deka, 2021). Pea

proteins can form gels and emulsions, as well as stabilize foams; therefore, they are useful in the production of PBMAs with desirable textural properties (Arora et al., 2023). Pea proteins, like soy proteins, are commonly utilized as isolates or texturized to obtain fibrous structures (Benkovic et al., 2023).

Wheat Protein

Protein in wheat is available in the form of gluten, which is primarily composed of two proteins, gliadin and glutenin. Gluten is a widely used protein source in the food industry due to its unique functional properties. Gluten is viscoelastic in nature, allowing for the formation of a resilient gel during extrusion processes. It can be used as a thickener, fortifier, and texturizing agent in PBMAs, and can help ensure product stability by specifically binding the fiber together in the protein matrix (Zhang et al., 2021). However, gluten is deficient in lysine, an essential amino acid that is abundant in soy, hence gluten and soy are often combined to improve the nutritional quality of PBMAs (Day et al., 2006). Chiang et al. (2019) found that PBMA blends with 30% wheat gluten mixed with soy protein produced physicochemical properties close to those of meat (as cited in He et al., 2020).

Rice Protein

Rice is one of the most widely consumed cereals globally and provides humans with various nutrients such as carbohydrates, proteins, vitamins, and minerals. Protein is the second most abundant macronutrient in rice, at approximately 6-7%. There are four fractions of rice proteins, namely glutelins, albumins, globulins, and prolamins, which are soluble in alkali, water, salt, and alcohol, respectively, with glutelins being the most dominant protein (Jayaprakash et al., 2022; Day, 2013). Rice protein isolates are highly nutritious and similar to casein and soy protein isolates; they are highly recommended for infants and the elderly because of their nutritional

quality, digestibility, and hypoallergenicity (Wang et al., 2018). Compared with soy protein, rice protein has a milder flavor without an unpleasant taste; however, like gluten, it is also deficient in lysine and is often supplemented with soy protein in PBMAs to improve nutritional profile (Detchewa et al., 2022; Lee et al., 2022).

Other Protein Sources

Soy protein, pea protein, and wheat gluten, as discussed, have been widely used individually and/or collectively in PBMA formulations because they can create meat-like textures and other desirable properties. However, from an environmental sustainability and food security standpoint, there is a pressing need to expand the use of proteins from other plant sources for making PBMAs (Day, 2013). Hence, other proteins from legumes (chickpea, lentils, beans, peanuts), cereals and pseudocereals (corn, oats, quinoa, amaranth, buckwheat), and oilseeds (hemp, sunflower, rapeseed, sesame) (Benkovic et al., 2023), although not as widely used, are quickly gaining traction in PBMA formulations.

Chickpea is a valuable source of plant protein, containing approximately 20-30% protein on a dry-weight basis, although variations occur depending on genotype, growing conditions, and processing (Jukanti et al., 2012; Begum et al., 2023). Despite containing all the essential amino acids, its protein quality is limited by low levels of sulfur-containing amino acids, particularly methionine and cysteine. Additionally, it contains relatively low levels of phytoestrogens (Day, 2013). Low water solubility and the pH dependence of its functional properties, such as gelation, emulsification, and foaming ability, are constraints associated with chickpea protein that can reduce its applicability in PBMAs. However, thermal, mechanical, or enzymatic treatments can help overcome some of these obstacles by modifying the protein (Benkovic et al., 2023). Lactic acid bacteria fermentation has been shown to improve chickpea

protein solubility and in vitro digestibility through structural modifications and protein hydrolysis (Liu et al., 2023). In addition to chickpeas, lentils, faba beans, mung bean, and lupine proteins also have strong emulsion and foam stabilization capacities, making them good alternatives to soy for certain PBMA forms. However, most of these legumes have lower gelling abilities than soy proteins, which limits their applications (Kyriakopoulou et al., 2021).

Additives

Like many processed foods, PBMAs use additives to improve quality and extend shelf life under recommended storage conditions. Food appearance, including color, is the consumer's first point of interaction and therefore a major contributor to perceived taste and overall product acceptance (Spence, 2015). The addition of colorants to PBMAs provides color, making them visually appealing and subsequently increasing consumer acceptability. Flavorings enhance overall flavor and aroma, while antioxidants and antimicrobials can prevent oxidation and discoloration, improving shelf life (Sha & Xiong, 2020). According to Benkovic et al. (2023), cumin, carotene, lycopene, and beetroot juice are some commonly used colorants in PBMAs; flavorings include spices, herbs, yeast extract, paprika, sugar, and mushrooms. Additionally, oils such as sunflower, coconut, and palm oils have been used to create meat-like sensory properties. Thickeners and stabilizers (structural ingredients) such as methylcellulose, xanthan gum, gellan gum, carrageenan, starch, and guar gums have also been reported as additives used in PBMAs (Romão, 2023).

Processing Techniques

Plant- and animal-based proteins must unfold, cross-link, and align to form microscopic and macroscopic fibers (Wild et al., 2014). Therefore, achieving meat-like texture and sensory properties in legume proteins typically requires intensive processing techniques, including

extrusion, shearing, spinning, and cross-linking, which align protein molecules into microfibrils that form fibrous structures (Day, 2013). Extrusion is the most widely used technique for producing PBMAs because it is highly productive, economical, versatile, energy-efficient, and scalable (Arora et al., 2023; Ozturk & Hamaker, 2023; Andreani et al., 2023).

Extrusion is a thermomechanical technique used to texturize plant proteins. As described by Singh et al. (2021), the extrusion process, using either a single- or co-rotating twin-screw extruder, consists of three steps: pre-conditioning the material outside the extruder, mixing/cooking inside the extruder barrel, and cooling in the die, during which structure formation occurs. Based on the amount of water added during extrusion to create the meat analog, extrusion techniques can be classified as either high-moisture or low-moisture processes. Low-moisture extrusion (<30% water) creates texturized vegetable proteins (TVP) called low-moisture meat analogs (LMMAs), which must be rehydrated before cooking and are therefore used as meat extenders. On the other hand, high-moisture extrusion (>50% water) directly creates meat analogs known as high-hoisture meat analogs (HMMAs), which are adequately hydrated during the extrusion process and are then frozen to retain the moisture (Singh et al., 2021; Zahari et al., 2021; Andreani et al., 2023).

Shear structuring (Couette cell) is a more recent technique that uses a shear cell to develop intensive shear in a cell-like geometry. The cell configuration resembles that of rheometers, employing either a cone-in-cone or cylinder-in-cylinder (Couette) design to produce meat alternatives. In this method described by Ozturk and Hamaker (2023), the lower cone rotates at a specified speed while the upper cone remains stationary. As the cell is sealed to reduce water loss during the process, the product is subjected to shear stress and elevated temperatures (95–140 °C) in the space between the cones. Typically, the sample undergoes

treatment for 15–20 minutes under these settings, followed by cooling and resting at ambient temperature for one hour (Krintiras et al., 2016).

Electrospinning is another commonly used technique for producing thin fibers by spinning concentrated plant proteins at high speeds to produce PBMAs. Singh et al. (2021) described it as an economical process in which a blend of protein solution and other polymers is prepared based on solubility, viscosity, conductivity, and other component properties. When all conditions are met, the polymeric solution forms a Taylor cone, which then generates fine threads or fibrils under an electric field. An attached collector can then collect these entangled polymers. Beyond these widely used techniques, others such as freeze structuring, 3D printing, and fermentation are also gaining traction in the PBMA industry.

Barriers to Consumer Acceptance

Despite the growing popularity of plant-based meat alternatives as a meal option for various groups of consumers with differing dietary preferences, including vegetarians, vegans, flexitarians, and even traditional meat-eaters, there is still considerable resistance from consumers when it comes to fully accepting these products. In a study involving over 2,500 people in the United States, conducted by Parry and Mitchel (2019) and reviewed by Szejda et al. (2020), taste was identified as the strongest motivator for the purchase intent of PBMAs for the majority of respondents, followed by health, sustainability, and animal welfare. Other sources indicate that enjoyment of meat is a significant barrier to including PBMAs in meat-eaters' diets, followed by health and convenience (Corrin & Papadopoulos, 2017). While sustainability and animal welfare have been identified as major drivers of PBMA acceptance among consumers, taste has consistently remained a major barrier that prevents new and/or existing consumer segments from trying new plant-based meat products (Giacalone et al., 2022; Appiani et al.,

2023). Depending on the type of consumer, health may be a driver or barrier to acceptance; for instance, for flexitarians and traditional meat-eaters who may be looking to reduce their meat consumption due to associated health risks, health may be a driver; conversely, it could be a barrier for other consumers who perceive PBMAs as unhealthy due to their processing and ingredients.

Taste and texture remain two of the biggest factors affecting consumer acceptance, despite ongoing efforts by product developers and food scientists to produce PBMA products with properties comparable to meat products; this issue persists (Andreani et al., 2023). Most flexitarians and traditional meat-eaters cite reasons such as a lack of sensory similarities between the meat analogs and their animal-based counterparts, including differences in flavor, texture, and appearance (Tso et al., 2021). PBMA consumers, including vegetarians and vegans, may also cite disappointing flavor profiles, blandness, and off-flavors, among others (Szenderák et al., 2022) For instance, Joshi and Kumar (2015) reported grassy, beany flavors caused by lipoxygenases, as well as bitterness and astringency from saponins and isoflavones in soy protein, as major disadvantages of soy-derived meat analogs. Jung et al. (2024) reiterated that the lack of fat and flavor in plant-based meat alternatives was the primary reason for the low popularity of PBMAs.

A health barrier exists because consumers perceive vegetarian diets as nutritionally unbalanced, as meat is thought to provide essential nutrients for proper bodily function (Corrin & Papadopoulos, 2017). Additionally, in the process of eliminating unpleasant flavors associated with high levels of legume proteins, numerous additives are added to PBMA formulations to mimic the sensory characteristics of meat; this leads to the inclusion of unusually long and

unfamiliar ingredient lists on product packaging, which creates a perception that those products are highly processed and/or unhealthy (Giacalone et al., 2022).

Drivers of Liking in Food Research

A product's market success depends not only on consumer liking but also on repeat purchases; it must consistently appeal to consumers to become a repeat purchase (Drake et al., 2023). For this reason, drivers of liking are a significant topic in sensory and consumer research since they support product optimization. They are the sensory attributes that most strongly contribute to consumer acceptance and overall liking (Moskowitz, 2001). A product's liking or acceptance depends on its sensory properties; therefore, to fully understand liking, researchers must investigate its drivers to create products that meet consumer expectations (Mahieu et al., 2022).

Early research on drivers of liking primarily relied on pairing hedonic tests, in which consumers score their overall liking of products alongside some form of sensory characterization (Mahieu et al., 2022). Conventionally, sensory characterizations or profiling are done by a descriptive panel, whose members are trained to evaluate products objectively. According to Lawless and Heymann (2010), the simple correlation between sensory scores and liking scores, when attributes are viewed monadically, shows the strength of the relationship between them and can also help identify drivers of liking. Statistical techniques, such as preference mapping and regression analysis, are then applied to connect the liking data to the sensory data, thereby identifying the drivers of liking (van Trijp et al., 2007; Greenhoff & MacFie, 1999, as cited by Meullenet et al., 2008). There are two primary approaches to preference mapping, which are primarily differentiated by the point of view they adopt: internal (hedonic data drives the orientation of product space) and external (sensory data drives the orientation of product space)

preference mapping (van Kleef et al., 2006). In internal preference mapping, the product space obtained is based on the liking data from consumers, and the sensory attributes are regressed into this space; however, in external preference mapping, the product space obtained is based on the sensory disparities between products, and the first two sensory dimensions obtained by multivariate analysis (usually PCA) are extracted, and the liking scores of each consumer are regressed into this space (Worch, 2013; Mahieu et al., 2022; Cariou et al., 2014). External preference mapping is therefore an approach used to identify drivers of liking because it aims at relating consumers' liking data to sensory data (Vigneau et al., 2014; Cariou et al., 2014; van Kleef et al., 2006). In generating the PCA map using multiple regression models, only the first two principal components are retained, which presents a limitation since the use of two principal components may result in poor fitting of the liking scores of a considerable number of consumers (Meullenet et al., 2008). As a solution, partial least squares regression (PLSR) has been recommended in place of PCA for determining the perceptual space (Martens & Næs, 1989, as cited in Cariou et al., 2014). PLSR is a multivariate statistical approach suitable for modeling relationships between sensory attributes (X-predictors) and hedonic ratings (Y-responses) (Chung et al., 2003; Nho et al., 2025). Unlike PCA, which is applied separately to each dataset, PLSR simultaneously models both X and Y to identify the combination of X variables that best explains the variation in Y (Chung et al., 2003).

Recently, advances in sensory methodologies have led to the adoption of newer consumer-based methods that are faster and can produce sensory characterizations comparable to those obtained from trained panels (Valera and Ares, 2012). In this case, both liking and sensory data come from the same consumers. Just-about-right (JAR) scales, which are analyzed using penalty analysis, in which the decrease in overall liking associated with deviations from the ideal

(JAR) intensity is evaluated, are one of such methods that can be used to identify drivers of liking (Xiong & Meullenet, 2006; Lawless and Heymann, 2010). Penalty analysis helps to identify the sensory attributes that have the largest influence on consumer liking, thereby providing directions for product improvement (Ares et al., 2017). JAR evaluations ask consumers to directly assess deviations from an ideal intensity, usually using 3-point or 5-point scales anchored from ‘‘much too weak” to ‘‘much too strong” with “just about right” as the midpoint (van Trijp et al., 2007; Lawless and Heymann, 2010).

Check-All-That-Applies (CATA) is another method where consumers are provided with a list of sensory terms across various modalities (appearance, texture, flavor) and asked to select those that apply to the specific sample being evaluated (Ares et al., 2017). The frequency of citation of each term used to characterize each sample is then used to derive a product description (Jaeger et al., 2020; Jaeger et al., 2015). Penalty-lift analysis, which was initially developed for the analysis of JAR data, has been extended to CATA data. Therefore, when CATA data are paired with liking ratings obtained from consumers in a single test, a penalty-lift analysis can be performed to identify drivers of liking. The principle behind penalty-lift analysis for CATA data is that liking scores are averaged across all observations (samples and assessors), for which each attribute is checked (present), and across those observations for which the attribute is unchecked (absent) (Meyners et al., 2013). The difference in mean overall liking due to an attribute's presence or absence estimates the average change in liking. Attributes associated with increased liking can be considered positive drivers (lifts), whereas attributes associated with decreased liking can be considered negative drivers (penalties). A major limitation associated with penalty analysis is its univariate nature, which leaves intercorrelations among attributes unaccounted for. Hence, some authors have also applied PLSR analysis to CATA data to address

this issue in identifying drivers of liking. Regression models require predictors to be numerical; otherwise, they are converted into dummy variables (a numerical variable that usually represents a binary categorical variable). Therefore, considering that CATA attributes are already coded as binary variables (0/1) they can be treated as dummy variables and used directly as predictors in regression analyses (Xiong & Meullenet, 2006).

Additionally, correspondence analysis is another statistical technique that can be applied to CATA data; it is a factorial method suitable for the analysis of contingency tables and is used primarily for exploration and graphical visualization of product differences when dealing with categorical data (Cochran, 1950, as cited by Rinnan et al., 2015). In the literature, many authors have identified drivers of liking for a wide range of product categories using CATA data in combination with liking data, including plant-based meat alternatives (Nho et al., 2025; Petrat-Melin & Dam, 2023; Nguyen et al., 2023), plant-based dairy products (Jaeger et al., 2023; Jaeger et al., 2024; Tong et al., 2025), dairy products such as yogurt, milk, and ice cream (Ares et al., 2014; Dooley et al., 2010), and wine (Dupas de Matos et al., 2024).

The Ideal Profile Method (IPM) has been described as a consumer-based sensory method in which consumers are instructed to rate products on their perceived intensity, followed by their ideal intensity for a list of given attributes, and they also rate their liking; therefore, each consumer provides a sensory profile, hedonic ratings, and their ideal profile for each product evaluated during the test (van Trijp et al., 2007; Worch et al., 2014; Worch & Ennis, 2013). This method has been recently adapted for use with CATA data to identify drivers of liking. For this variant, the CATA study includes questions on liking, CATA attributes for each sample, and the selection of attributes for the ideal product using the same CATA list at the end of the test. Penalty analysis is then used to analyze the data, but this differs from the previously discussed

penalty-lift analysis, as it is based on the differences between real and ideal products and the impact on liking scores (Meyners et al., 2013). In this approach, developed by Ares et al. (2014), if an attribute is checked for either the ideal or the evaluated product but not both, then there is disagreement (deviation from the ideal), and it is coded as one (1). However, if an attribute is checked for both or not checked for either, then there is agreement, and it is coded as zero (0). The difference in mean liking between consumers who agree with the ideal and those who deviate from the ideal is then determined. This value represents an estimate of the average impact on liking (mean drop) resulting from deviations from the ideal. To determine drivers of liking, the percentage of consumer deviations for each attribute is calculated across products; this is followed by performing a non-parametric statistical test such as the Kruskal-Wallis test (each CATA attribute as the factor and overall liking as the dependent variable), to establish whether deviation from the ideal for each attribute is associated with a significant decrease in overall liking (Ares et al., 2014; Plaehn, 2011). Consequently, attributes that deviate from the ideal for more than 20% of consumers and are associated with a significant decrease in overall liking are considered drivers of liking, consistent with the interpretation of JAR-based penalty analysis results (Xiong & Meullenet, 2006).

In addition to the previously discussed consumer-based methods, others such as preferred attribute elicitation (Grygorczyk et al., 2013), external preference mapping based on free sorting (Faye et al., 2006), preference mapping based on CATA (Dooley et al., 2010), Free-JAR profiling (Le et al., 2020), and ideal Free-comment (Mahieu et al., 2022), among others, have been used in the literature to identify drivers of liking and characterize the ideal product. Although all these methods have limitations, they can ultimately help provide a deeper

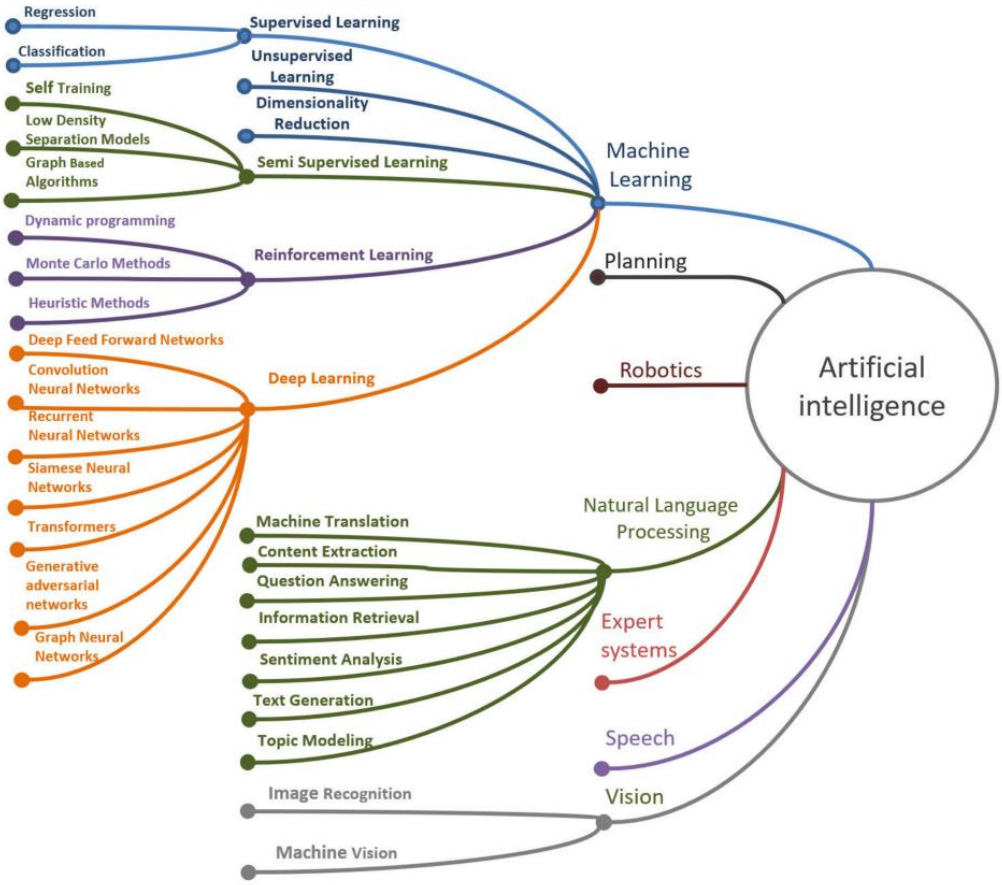
understanding of the product attributes that drive consumer preferences, thereby supporting product improvement and optimization.

Artificial Intelligence Applications in Sensory and Consumer Research

Artificial intelligence (AI) is a scientific field that pursues the development of intelligent systems that mimic aspects of human behavior through techniques inspired by nature (Nunes et al., 2023). AI includes several major scientific areas, such as machine learning and natural language processing (NLP), text and speech synthesis, computer vision, robotics, planning and expert systems (Mukhamediev et al., 2022) as illustrated in Figure 1.1.

Due to their widespread applications and benefits, AI-based systems have been widely explored and applied in many fields in recent years. Advances in AI have led to new opportunities to enhance and expand the scope of sensory evaluation. Jo et al. (2025) conducted a review on advances in AI in sensory evaluation. They concluded that AI enables advanced modeling of human sensory perception by connecting analytical data with consumer sensory data. It was also emphasized that predictive modeling of sensory attributes is facilitated by machine learning and deep learning, while computer vision and e-sensing technologies can reproduce aspects of human visual and chemical perception. Additionally, natural language processing makes the extraction of sensory information from consumer-generated text possible. Figure 1.2 provides a summary of the major AI technologies that have been applied in sensory evaluation according to the authors.

Figure 1.1: Subsections of artificial intelligence.

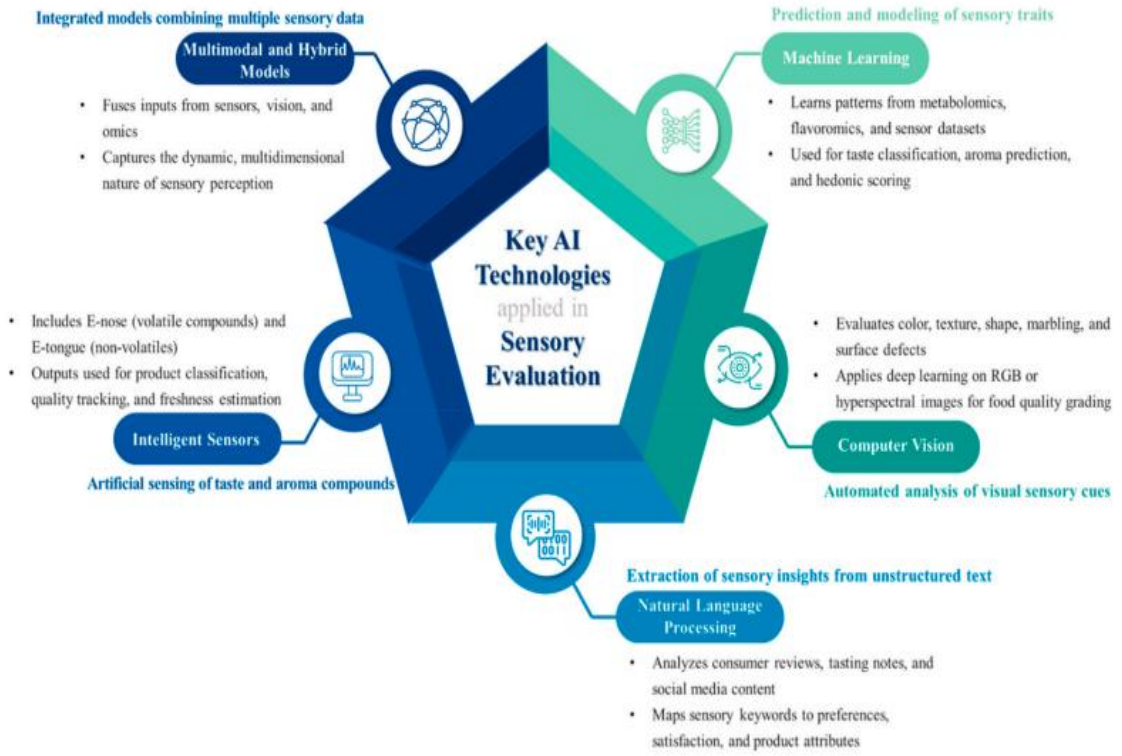


Source: Mukhamediev et al., (2022).

More recently, Nunes et al. (2023) also reviewed the applications of AI-based solutions in sensory and consumer studies of food products. They highlighted that most AI applications in sensory and consumer science utilize machine learning (ML) to predict the intensity of sensory attributes (sweetness, acidity, juiciness, etc.), acceptance, and consumer preferences from non-sensory data such as physical, chemical, and instrumental measurements. They also highlighted the integration of AI with computer vision and robotics, electronic sensors, and biometric technologies to assess appearance, aroma, flavor, and consumer emotional responses to food and food packaging, facilitating the automation of large-scale data acquisition and analysis.

Additionally, the review highlighted the more recent AI-based analysis of large consumer datasets, such as online reviews and social media posts about food products, which helps researchers understand public perception and sentiment towards food products, expanding sensory research beyond controlled sensory testing. Despite these advancements, the authors noted that the full potential of AI has not been realized in sensory and consumer research, as the majority of applications use AI at the basic level.

Figure 1.2: Summary of key AI technologies applied in sensory evaluation.



Source: Jo et al. (2025).

As mentioned earlier, the majority of the applications of AI in sensory science have employed machine learning techniques to address research questions relevant to sensory and consumer science (Saenz-Navajas et al., 2025; Zhu et al., 2025; Lu et al., 2025; Harris et al., 2025; Zou et al., 2024). Throughout these studies, the high predictive performance of ML

technologies using large-scale datasets was repeatedly demonstrated across multiple food categories, positioning these technologies as valuable complementary tools to conventional sensory techniques.

Text mining and natural language processing (NLP) have recently been utilized by researchers to aid in the extraction and processing of sensory data from large amounts of unstructured online text, potentially reducing the need for repeated sensory testing (Chen et al., 2021). This provides an approach to addressing the frequently cited limitation of the restrictive nature of using predefined sensory terms, which may limit the ability to capture all perceived sensory dimensions during consumer-based sensory evaluation techniques. NLP, an approach related to text mining and rooted in AI, computer science, and linguistics, systematically analyzes language through text preprocessing, syntactic structures, and semantic analysis, enabling the interpretation of consumers' free-form and ambiguous textual expressions (Lee et al., 2025).

NLP and text mining have been used to obtain sensory insights such as descriptors, emotions, sentiments, and drivers of liking from consumer texts (online reviews, free comments, etc.) to understand consumer behavior towards different products and to predict consumer preferences, including coffee (Espinosa-Ramos et al., 2025), whisky (Hamilton & Lahne, 2020; Hamilton et al., 2023), and chocolate (Mahieu et al., 2020). These studies, along with others that have adopted NLP-based approaches in literature, demonstrate that it is possible to extract meaningful sensory data from consumer texts.

Deep learning (DL) is a subset of machine learning that has also recently been applied in sensory science to predict and classify sensory attributes and flavor. It facilitates the prediction and classification of unknown data by allowing computers to automatically extract features from

large datasets (Su et al., 2024). Large language models (LLMs) are AI models based on DL, trained on large amounts of data, primarily natural language text, to generate human-like text outputs (Lee et al., 2025). This allows LLMs to handle a broad range of language-based tasks, including translation, text summarization, and content generation (Motoki et al., 2025). Examples of LLMs include models from the GPT, PaLM, Llama, Gemini, and Claude families, among others.

In a recent study, Torrico (2025) used ChatGPT as a sensory evaluator of fifteen hypothetical chocolate brownie formulations. This study showed that ChatGPT expressed more positive emotions toward the formulations than real consumers. Like many authors, Torrico (2025) reiterated the importance of validating ChatGPT sensory responses with actual consumers or a sensory panel, considering that LLMs may interpret product attributes differently from actual consumer perception. Motoki et al. (2024) also examined cross-modal correspondences between colors, shapes, and tastes in ChatGPT-3.5 and GPT-4o using generated silicon samples obtained in three languages (English, Japanese, and Spanish). They found that GPT-4o consistently associated colors and shapes with basic tastes across the three languages, with some differences compared to what has been previously observed in human participants.

Limitations still exist in fully capturing and interpreting consumer data that reflect diverse emotions and experiences, despite the ongoing evolution of AI-based technologies and their applications in sensory and consumer research. To mitigate the risk of model bias associated with biased or unrepresentative training datasets, AI systems must draw on diverse sources of information and perspectives, alongside adequate human verification to reduce the generation of inaccurate outputs (Lee et al., 2025). This necessitates the adoption of an integrated

framework in which AI-based analyses and human sensory data are used to complement each other.

Online Product Reviews as a Source of Sensory Information

A product review is a text, mostly written, provided by a consumer to describe their experience with a product, typically comprising both quantitative (e.g., a 5-star rating) and/or qualitative components (e.g. a text narrative) (Agnihotri & Bhattacharya, 2016; Reed et al., 2019). Because customer ratings and reviews are a highly desirable and efficient form of word-of-mouth communication (Picazo-Vela et al., 2010), popular e-commerce companies such as Amazon, and eBay, as well as omnichannel companies such as Walmart and Target, among others, have incorporated online customer ratings and reviews into their marketing strategies. These user-generated reviews and ratings serve as a guide, helping potential consumers predict product quality before purchase, which explains why the average rating has become a significant driver of sales across several product categories (deLanghe et al., 2016; Picazo-Vela et al., 2010). People tend to have different motivations for writing reviews; not everyone who purchases a product or service leaves a review, although there is a higher likelihood that a person who has had an exceptional experience, whether positive or negative, will write a review (Espinosa-Ramos et al., 2025).

Consumers use online reviews as a means to share various information about their product experiences, ranging from sensory appeal and product functionality to usability, delivery experiences, value for money, and product changes, among others. In a study by Lopez and Garza (2022), the influence of reviews on consumers and the extent to which people found them helpful were investigated. They analyzed over 400,000 Amazon reviews across different product categories and performed a topic modeling analysis to extract the main topics that consumers

expressed in their reviews. After identifying the main topics, they used them as regressors to predict the number of consumers who found the reviews helpful and therefore may have been influenced by the reviews in making their consumption decisions. They found that consumers review products based on their sensory experiences, as well as on more practical properties, such as the product's performance, features, and the installation or setup process.

The potential use of online reviews as a source for generating sensory information about products is gradually being explored by some authors in the literature. Generally, the extraction of sensory descriptors or information from reviews involves a series of standard steps, including scraping the reviews, cleaning the text, and processing the text (e.g., term clustering or grouping) to identify key sensory attributes.

Reed et al. (2019) analyzed over 390,000 reviews written by 256,043 people about 62,750 food products on Amazon to investigate the role of taste in commercial products. They found that taste-related words were mentioned more frequently than words associated with price, food texture, customer service, nutrition, smell, or mouthfeel attributes. The terms taste, sweet, bitter, sour, and salty were mentioned in over 30% (N = 142,768), 10.7% (N = 42,315), 2.9% (N = 11,424), 2.1% (N = 8,252), and 1.4% (N = 5,688) of the reviews, respectively. They also compared the texture terms to those used by sensory panels to describe texture and found substantial agreement.

Hamilton and Lahne (2020) utilized natural language processing (NLP) to collect, clean, and extract sensory descriptors from over 6,500 online reviews of international whiskies from two prominent whisky websites. They generated an attribute list, which was grouped into a flavor wheel using correspondence analysis and agglomerative hierarchical clustering, and compared the wheel to an existing Scotch whisky flavor wheel. They found that their wheel

reproduced the majority of the sensory dimensions of the existing wheel but excluded certain non-aromatic categories. Hence, they concluded that their wheel was suited for product positioning and exploratory research, but not for quality control.

Yang et al. (2021) also compared data mining and subsequent visualization of sensory terms from online reviews (about 1.4 million words) collected from two prominent Chinese websites with the assessments from a trained panel (QDA) for Chinese mitten crabs from different regions in China. They found that the reviews were able to identify which crab sample was liked the most due to its association with the basic tastes of sweet and umami (based on the frequency of mentions in the reviews). This was confirmed by the trained panel assessment, although the trained panel provided more detailed insights by quantifying the sensory differences between the crabs. They therefore concluded that while visualization of online reviews was quicker, it was more qualitative in nature, whereas the trained panel assessment, although more laborious, was more informative.

More recently, Espinosa-Ramos et al. (2025) utilized natural language processing to analyze online reviews of five unflavored coffee products, each with a minimum of 1,000 reviews. They compared the resulting sensory profile to one generated through a CLT with 105 consumers using rate-all-that-apply (RATA) questions. They were successful in developing a sensory profile based on the online reviews, which was able to differentiate the samples used in the study, although the terms were mostly intensity-related rather than descriptive. Except for some differences in the characterization of specific sensory attributes, both methods yielded similar product differentiation. Their findings indicated that the review-based method captured sensory terms in a consistent and meaningful way, similar to the RATA method used with consumers.

These studies show that online reviews may contain valuable sensory information that can be leveraged to support product development efforts. However, due to the uncontrolled and heterogeneous nature of review data, their use may be more suited to providing preliminary guidance or to the exploratory phases of product development and improvement research. In most cases, validation against conventional sensory methods is still required. Nonetheless, further research is needed to better understand the reliability, limitations, and full potential of sensory information collected from online reviews.

Research Objectives

Despite the rapid growth and the influx of different categories of PBMAs on the market, the sensory properties of these products remain among the biggest barriers to their acceptance. Online reviews have been shown to contain information about consumer experiences and preferences, and hence, analyzing them may provide valuable insights into the sensory attributes that drive consumer liking and disliking. AI techniques such as NLP have been used to extract sensory information from unstructured consumer texts; however, the process of extracting, cleaning, and processing such large amounts of text has been reported to be time-consuming and to require expertise. LLMs such as ChatGPT are driven by user prompts and may be able to rapidly extract relevant information from these reviews. Despite the application of ChatGPT in various fields, to date, no research has explored the use of this technology to analyze online reviews of PBMAs to determine their sensory drivers of liking and to compare with drivers of liking identified through conventional sensory approaches.

This research has three general objectives:

1. To identify drivers of liking of plant-based meat alternatives using Check-All-That-Applies (CATA).
2. To identify drivers of liking of plant-based meat alternatives from e-commerce reviews and ratings using ChatGPT.
3. To compare the drivers of liking identified using CATA with those identified from e-commerce reviews and ratings using ChatGPT.

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Chapter 2 - Consumer Research and Check-All-That-Apply (CATA) Drivers of Liking of Plant-Based Meat Alternatives

Abstract

This study aimed to identify the sensory attributes driving consumer acceptance of plant-based meat alternatives (PBMAs) using Check-All-That-Apply (CATA) methodology, while also evaluating consumer-perceived benefits and concerns. Understanding these drivers is important because sensory acceptance strongly influences repeat purchase, making it essential for product development and market success. A central location test was conducted with 100 consumers in the Kansas City Metro area, where each consumer evaluated 6 plant-based chicken samples formulated with various proteins. The consumer test revealed statistically significant differences ($p < 0.05$) across all measured liking indices, with formulations containing pea protein associated with higher consumer liking scores. Partial least squares regression and penalty analysis were both used to determine drivers of liking from overall liking and CATA attribute frequencies. Attributes including “meaty/savory”, “chicken-like”, “spice/herb”, “toasted/brown”, “crispy”, “tender”, “crunchy”, and “moist/juicy” were identified as consistent positive drivers of liking, whereas “cardboard” significantly reduced acceptance. Comparison of the statistical methods revealed that the multivariate Partial Least Squares Regression (PLSR) generated a more conservative selection of significant drivers than univariate penalty-lift analysis by accounting for inter-attribute correlations. Beyond sensory properties, consumers identified perceived health benefits, affordability, and versatility in meal and flavor options as the primary reasons for trying new PBMAs, whereas taste, high cost, and ultra-processing were major deterrents. Overall, while consumer interest in PBMAs remains strong, improving acceptance

may depend on optimizing sensory quality, more specifically flavor and texture, while delivering affordable and minimally processed formulations.

Introduction

Global meat consumption is estimated to increase by 14% by 2030 due to the rapid expansion in world population and income growth in developing economies (OECD/FAO, 2021). this projected increase is expected to occur alongside constraints on meat production capacity due to large portions of fertile land already used for livestock farming, as well as growing concerns about the environmental implications of livestock production, animal welfare, and public health associated with high-volume herding and slaughtering (Post, 2012; Nijdam, 2012). Additionally, factors inherent to consumer behavior, such as the growing demand for healthier dietary options, concerns over rising meat prices, the rising prevalence of vegetarianism, and increasing interest in related eating patterns such as the reduction or avoidance of red meat consumption, have amplified the demand for sustainable meal solutions from non-animal sources **(**Joshi & Kumar, 2015).

As a direct response, the plant-based meat alternatives (PBMAs) industry has been experiencing rapid growth, with a wide variety of products being manufactured to mimic their meat counterparts. Between 2017 and 2019, the US PBMA industry grew significantly, and by the end of 2019, it was worth about US$939 million (Choudhary et al., 2020). According to a 2025 market report by the IMARC Group, the global market for PBMAs was estimated at US$16.7 billion in 2024 and is projected to reach US$100.3 billion by 2033, representing a compound annual growth rate of about 21.92% from 2025 to 2033 (IMARC Group, 2025). In the US market, PBMAs are produced and marketed by companies such as Impossible Foods, Beyond Meat, Gardein, Lightlife, Morningstar Farms, Dr. Praeger's, and Hampton Creek, as plant-based chicken (chik'n), beef, burgers, patties, bacon, and sausages, just to name a few. These products are primarily formulated with water, proteins from plant sources (pea, soy,

wheat, rice, etc.), and additives including binders, colorants, extenders, flavor enhancers, and stabilizers; however, the specific ingredients depend on the animal product they are made to imitate (Kyriakopoulou et al., 2021; Ahmad et al., 2022).

Despite systematic efforts, such as the use of advanced ingredients and processing technologies such as extrusion, to produce these PBMAs, their nutritional and sensory appeal, among other factors remain barriers to adoption. Several studies have consistently identified taste, texture, and other sensory attributes as major factors affecting consumer acceptance of PBMAs (Hoek et al., 2011; Elzerman et al., 2013; Andreani et al., 2023). This underscores the importance of studying consumer acceptance and understanding the drivers of consumer choices to optimize these attributes and support market success and repeat purchases of new PBMAs. Sensory and consumer science offer valuable tools for identifying barriers to consumer acceptance of specific plant-based products and determining the product attributes that drive consumer preference.

When the sensory attributes of PBMAs are paired with hedonic or liking data, various statistical analyses can be performed to identify which attributes strongly impact consumer liking, known as the drivers of liking. Conventionally, drivers of liking have been identified by combining descriptive analysis performed by trained panels, with consumer acceptance evaluations, followed by statistical analyses such as external preference mapping or partial least squares regression analysis (Mahieu et al., 2022; Villamor et al., 2013; Vigneau et al., 2014; Cariou et al., 2014; van Kleef et al., 2006; Chung et al., 2003). However, with advances in sensory methodology, newer consumer-based methods have emerged that provide more rapid approaches to sensory characterizations without requiring trained panels.

Check-All-That-Apply (CATA) is one of the consumer-based sensory methods that has been widely adopted to characterize the sensory attributes of food using consumers, due to its simplicity and ability to capture consumer perception (Ares et al., 2014). In this method, consumers are presented with a list of terms relevant to a product group or category and instructed to select all terms that describe each product. The frequency of citation of each term used to characterize each product is then used to derive a product description (Jaeger et al., 2020; Jaeger et al., 2015). When hedonic data are paired with CATA data derived from consumers in the same test, statistical analyses can be performed to identify drivers of liking. Additionally, CATA questions can be used by consumers to describe the sensory characteristics of their ideal product (Ares et al., 2014), which allows researchers to identify sensory characteristics associated with liking, overall and for different consumer segments (Ares & Jaeger, 2022). Numerous authors have successfully employed CATA to identify drivers of liking for various categories of plant-based meat alternatives. For instance, Ettinger et al. (2022) identified crunchy, crispy, soft, savory, salty, juicy, and a lack of aftertaste as drivers of liking of plant-based chicken nuggets (a control chicken-based nugget was also evaluated in the study). More recently, Nho et al. (2025) also identified the following attributes as drivers of liking for plant-based tteok-galbi: glossy appearance, sweet taste, umami taste, meaty odor/flavor, smoked flavor, elasticity of mouthfeel, and oily mouthfeel.

Penalty-lift analysis is the simplest statistical approach to relate hedonic scores to CATA data (Meyners et al., 2013). It was originally developed for analyzing Just-About-Right (JAR) questions but has since been extended to CATA data as proposed by Plaehn (2012). This approach helps identify drivers of liking by comparing the mean overall liking scores when an attribute is checked versus unchecked by consumers. This technique has been widely employed

and successfully used to identify drivers of liking for a wide range of products, including bread (Meyner et al., 2013), fruits (Tarancón et al., 2020), soda (Plaehn, 2012), and plant-based chicken nuggets (Ettinger et al., 2022), etc. While it is a helpful tool, a major limitation is that it is univariate in nature and hence ignores correlations between product characteristics, which implies that attributes that may not be true drivers could appear to be drivers if they are highly correlated with a true driver (Xiong & Meullenet, 2006). Partial least squares regression (PLSR) is a complementary multivariate approach, well-suited for modeling relationships between sensory predictors and hedonic responses (Chung et al., 2003; Nho et al., 2025). It provides regression coefficients and Variable Importance in Projection (VIP) scores (Rossini et al., 2012), enabling the identification of attributes that are positively or negatively associated with overall liking. These two techniques, when used together, can provide deeper insights into the drivers of liking of plant-based meat alternatives.

This research aimed to identify and understand the sensory characteristics of plant-based meat alternatives that drive consumer acceptance. To achieve this, Check-All-That-Apply (CATA) questions were used to characterize the sensory attributes of a variety of plant-based chicken products, including chicken tenders, chicken nuggets, and chicken pieces, as well as an ideal product. Penalty-lift analysis and partial least squares regression were applied to CATA data for a comparative assessment of sensory drivers associated with consumer acceptance, particularly those related to texture, flavor, and mouthfeel.

Materials and Method

Samples

Six commercially available plant-based chicken products were selected for evaluation. The samples were purchased from a local grocery store the week before the consumer study was conducted and stored in a freezer (0°F) until the day of the study. All the samples were labeled as plant-based chicken pieces, and consisted of three plant-based chicken tenders, two plant-based chicken nuggets, and one plant-based chicken piece product coded PBC1 to 6 (Table 2.1). Samples were selected based on the criterion that they had at least 50 reviews on Amazon, an e-commerce platform. Samples were cooked either in an oven (PBC1,2,4,5,6) or a skillet (PBC3) according to the package instructions, within 20 minutes prior to serving, and were stored in a food warmer. All the samples were served hot at about 145°F.

Participants

A total of 100 consumers (37 men and 63 women) between the ages of 18 and 75 from the Kansas City area, whose demographics are shown in Table 2.2, were recruited through a database maintained by the Sensory and Consumer Research Center at Kansas State University Olathe (Kansas, USA) using Compusense software (Compusense Inc., Guelph, Ontario, Canada). Participants were screened for gender, age, food allergies, grocery shopping habits, previous participation in consumer testing, and willingness to taste plant-based chicken-like products. Dietary preferences (e.g., vegetarian, omnivorous, and flexitarian) were not included as an exclusion criterion during screening to allow for a diverse group of consumers with different dietary preferences. At the end of the screener, participants who met the screening criteria were allowed to schedule themselves based on their availability for one of four study sessions, each scheduled one hour apart and lasting thirty-five (35) minutes. All four (4) sessions were held on

a single day, during which consumers evaluated all six (6) products and were compensated for their time upon completion. Eligible participants were non-pregnant men and women aged 18-76 with no food allergies, who were household grocery shoppers, had consumed plant-based chicken products within the past month, were willing to try PBMAs, and had not participated in a consumer study in the previous three months. Individuals working in food service or advertising were excluded to prevent bias.

Table 2.1: Plant-based chicken-like products and ingredients listed on product packages

Product	Product name	Raw Material in Ingredient list
PBC1	Impossible chicken nuggets	Water, **wheat flour**, **soy protein concentrate**, sunflower oil and soybean oil, 2% or less of: potato starch, methylcellulose, natural flavors, salt, cultured dextrose, **wheat gluten**, yeast extract, yellow corn flour, dextrose, food starch modified, sugar, garlic powder, onion powder, spices. leavening (cream of tartar, sodium bicarbonate), dried yeast, paprika extract (for color), vitamin e (tocopherols). vitamins and minerals: zinc, vitamins (B3, B5, B1, B6, B2, and B12)
PBC 2	Gardein plant-based seven grains crispy Tenders	Water, enriched **wheat flour** (wheat flour, niacin, reduced iron, thiamine mononitrate, riboflavin, folic acid), **soy protein isolate**, canola oil, **vital wheat gluten**, 2% or less of : rice flour, oat bran, methylcellulose, salt, oats, sugar, sunflower oil, ancient grain flour (Khorasan wheat), spices, quinoa flour, amaranth flour, millet flour, potato starch, natural flavors, leavening (sodium bicarbonate, cream of tartar), yeast extract, titanium dioxide(color), yeast extractives of paprika (color), lactic acid.
PBC3	Daring original plant chicken	Water, **soy protein concentrate**, vegetable oil (sunflower and/or canola), salt, natural flavor, spices (paprika, pepper, ginger, nutmeg, mace, cardamom)
PBC4	Gardein Ultimate Plant-based Chik'n Tender	Water, enriched **wheat flour** (wheat flour, niacin, reduced iron, thiamine mononitrate, riboflavin, folic acid), **vital wheat gluten**, canola oil, **soy protein isolate**, **pea protein concentrate**, tapioca starch, 2% or less of: degeminated yellow corn flour, **textured wheat protein** (wheat gluten, wheat starch), methylcellulose, salt, yeast extract, natural flavors, garlic powder, spices, dried onion, fructose, leavening (sodium acid pyrophosphate, sodium bicarbonate), paprika extractives(color), pea protein, onion powder, citric acid, titanium dioxide(color), xanthan gum, lactic acid, sunflower oil
PBC5	Beyond chicken tenders	Water, enriched **wheat flour** (wheat flour, niacin, reduced iron, thiamine mononitrate, riboflavin, folic acid), **wheat gluten, pea protein**, modified corn starch, 2% or less of potato starch, natural flavors, expeller-pressed canola oil, methylcellulose, salt, rice flour, cellulose fiber, coconut oil, onion powder, yeast extract, oat bran, spices, dried garlic, oat fiber, dried yeast, paprika, sugar, garlic powder, potassium salt, dried onion, dextrose, leavening (sodium acid pyrophosphate, baking soda), citric acid
PBC6	Morning Star Farms chik'n nuggets	Water, **wheat flour**, **soy protein concentrate**, vegetable oil (corn, canola and/or sunflower), **soy protein isolate**, contains 2% or less of: methylcellulose, salt, **wheat gluten**, yellow corn flour, potato starch, natural flavors, maltodextrin, pea starch, potassium salt, wheat starch, yeast extract, sugar, rice flour, dextrose, spices, onion powder, paprika color, garlic powder, leavening (sodium acid pyrophosphate, sodium bicarbonate), yeast, citric acid

***** *Ingredients shown in bold indicate the primary protein source identified for each product based on the ingredient list provided on the product packaging*.

Questionnaire

The questionnaire was designed and administered using Compusense software (Compusense Inc., Guelph, Ontario, Canada), and participants were required to sign in with their usernames and passwords. Informed consent was obtained from each participant (IRB-13678) before they completed the questionnaire, which consisted of liking questions, Check-All-That-Apply (CATA) questions, and an open-ended question. The hedonic questions were related to appearance, aroma, overall flavor (including mouthfeel), texture, and aftertaste. Participants were asked to rate their responses on a 9-point hedonic scale (1 = dislike extremely; 9 = like extremely). For the open-ended question, consumers were asked to comment on the sensory properties of the plant-based chicken product they were evaluating. The open-ended question was asked before the CATA question to see if consumers would come up with different terms to describe the products. The CATA questions were grouped into flavor and mouthfeel (21 terms); Salty, Meaty/ Savory, Chicken-Like, Beany, Sweet, Soy, Sour, Oily, Grainy, Onion, Spice/ Herb, Cardboard, Fishy, Mouth-Burn, Green/ Vegetable, Toasted/ Brown, Rancid, Aftertaste, Mouth-Drying, Bitter, and Particle Residue; and texture (11 terms); Chewy, Crispy, Tender, Dry, Firm, Crunchy, Moist/ Juicy, Greasy, Gritty, Tough, and Toothpacking . These terms were used to collect data on which sensory attributes were perceived by consumers in each of the six products. After answering the questions about their last sample, consumers were given the same CATA ballot and asked to check which attributes they believed an ideal plant-based chicken piece should have. The presentation order of the terms was randomized between and within participants. CATA terms were selected from the literature based on previous plant-based meat alternatives studies and refined during a 1-hour technical evaluation session by four sensory scientists at the Sensory and Consumer Research Center at Kansas State University Olathe

(Kansas, USA). In the demographics section of the questionnaire, participants were asked about their age, gender, dietary preferences, frequency of plant-based chicken consumption, and benefits and concerns regarding plant-based meat alternatives.

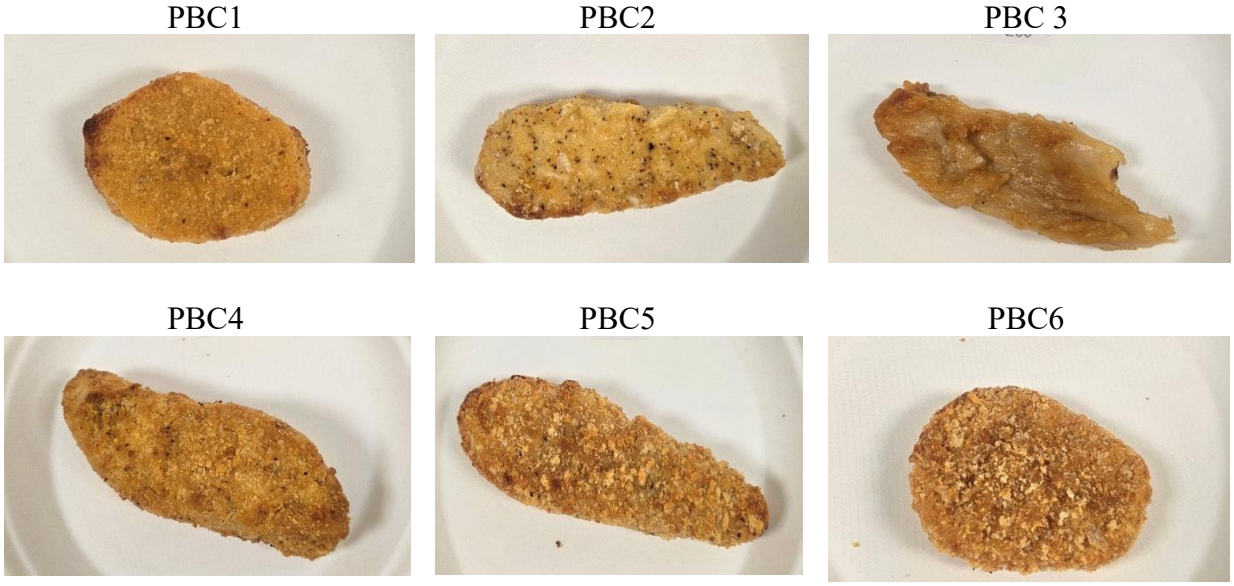
Table 2.2: Consumer demographics (N = 100)

Characteristics	Categories	Number of Participants
Age	18 – 25	3
	26 – 35	8
	36 – 45	23
	46 – 55	28
	56 – 65	21
	66 – 75	17
Dietary Preference	Vegan	1
	Flexitarian	15
	Vegetarian	8
	Pescatarian	3
	Omnivore	24
	Carnivore	38
	I do not know	11
Consumption Frequency of PBMAs	More than once a week	13
	Once a week	21
	2 to 3 times a month	31
	Once a month	18
	1 to 2 times a year	14
	Less than once a year	1
	Never	2

Evaluation Procedure

Each participant evaluated all six plant-based chicken pieces. The samples were served randomly in a sequential monadic order, with the serving order balanced across participants. There was a timed 2-minute delay between servings. Before the first sample, and between subsequent samples, participants had a bite of an unsalted saltine cracker and took a sip of water to cleanse their palates. Samples were served blind on 3-digit-coded 6-inch paper plates. The serving size was one piece of each sample.

Figure 2.1: Plant-based Chicken samples used in study



Data Analysis

Analysis of Variance (ANOVA) was performed on liking data, and Fisher's least significant difference (Fisher's LSD) was used for pairwise comparisons. The citation frequencies of attributes in the CATA list were determined for each sample. Cochran's Q-test was used to determine whether the citation frequencies of each CATA attribute differed significantly among the plant-based chicken products. This was followed by multiple pairwise comparisons using the Sheskin procedure. Only the significant attributes from this test were used for all further analyses pertaining to them. Correspondence analysis (CA) was then performed on the contingency table, with samples as rows and CATA terms as columns, using chi-square distances to generate a sensory map visualizing the relationships between them.

Penalty analysis and partial least squares regression (PLSR) were used to identify drivers of liking**.** Penalty-lift analysis was performed on the CATA attributes and overall liking data to evaluate the difference in overall liking when each attribute was selected versus not selected (Meyners et al., 2013). Additionally, PLSR was performed on CATA data and overall liking data

to identify drivers of liking. The frequencies of CATA attributes were treated as independent variables (predictors) and overall liking as the dependent variable (response) (Nho et al., 2025). Open-ended (OE) comments were analyzed using R (R Core Team, Vienna, Austria) to provide a visual summary of the most frequently mentioned terms. The tidyverse and tidytext packages were used to process the text, and the wordcloud package was used to create a word cloud. Only words that occurred at least three times throughout all responses were included in the word cloud. All other statistical analyses were performed in XLSTAT software (Addinsoft, New York, USA). Statistical significance was set at $p<0.05$

Results and Discussion

Consumer Liking

Significant differences were observed among samples on all measured hedonic indices as shown in Table 2.3. Using a 9-point scale, consumers rated the six plant-based chicken samples, with ratings ranging from 2.37 (dislike very much) to 7.62 (like very much) across all measured indices. PBC4 and PBC5 received the highest significant ratings across most of the measured parameters, whilst PBC3 consistently received the lowest ratings across the board. PBC3 was the only unbreaded chicken product among the six samples, hence it was physically distinct from the others. Apart from the fact that the other five samples were breaded, what they all had in common was that they were formulated with multiple plant proteins, and they all contained wheat gluten (Table 2.1) which was not present in PBC3. PBC3 had a very simple formulation and was made with only soy protein (concentrate). While soy protein is undoubtedly a top plant protein choice used in PBMA formulations due to its ability to create a desirable meat-like texture, it has been reported that when soy protein is combined with the right amount of wheat

gluten, it could produce PBMAs, whose physicochemical properties are close to meat (Chiang et al., 2019, as cited by He et al., 2020). The presence of both soy protein concentrates and wheat gluten in PBC1 and PBC6 may have contributed to sensory differences from PBC3; however, because these commercial products differed in multiple formulation and processing factors, the differences in liking cannot be attributed specifically to their protein composition. Additionally, PBC2, 4, and 6 contained soy protein isolates, which have been reported to increase preference for PBMAs when present at higher levels (Ahmad et al., 2022). Despite having a higher concentration of soy protein isolate, PBC2 received significantly lower ratings across all indices than PBC4, as did PBC6. Both PBC4 and PBC5, which received the highest significant ratings for most attributes, were formulated with pea protein. Although this observation is consistent with findings reported by Nho et al. (2025), the higher acceptance of PBC4 and PBC5 cannot be attributed specifically to pea protein because the products differed in multiple formulation characteristics. Overall, these results demonstrate substantial differences in consumer acceptance among the PBMA formulations evaluated, which may reflect differences in protein sources as well as other ingredients, processing, breading, and overall product formulation.

Table 2.3: Consumer liking results from the evaluation of plant-based chicken pieces on a 9-point hedonic scale (N = 100)

Product	Appearance Liking	Aroma Liking	Overall Liking	Flavor Liking	Texture Liking	Aftertaste Liking
PBC1	6.87b	6.19b	6.01ab	5.96ab	5.99ab	5.81a
PBC2	5.72d	5.84b	5.04c	5.05c	5.26c	5.11b
PBC3	2.99e	4.58c	2.76d	2.90d	2.37d	3.35c
PBC4	7.62a	6.87a	6.37a	6.14a	6.44a	5.78a
PBC5	6.70bc	6.96a	6.17a	6.00ab	6.41a	5.82a
PBC6	6.37c	6.81a	5.60b	5.50bc	5.70bc	5.02b
Pr > F(Model)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

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

CATA Sensory Profiling

According to Cochran's Q test, there were significant differences ($p < 0.05$) in the frequency with which 24 of the 32 CATA terms were used to describe the PBMA samples, suggesting that consumers perceived differences in the sensory characteristics of the evaluated samples. The exceptions were "beany", "sweet", "soy", "sour", "green/vegetable", "bitter", "firm", and "toothpacking", for which there were no significant differences ($p > 0.05$) in frequency between the samples. The frequencies of checked CATA attributes associated with each sample by consumers are shown in Table 2.4. "Toasted/brown" was the most selected attribute used to describe all the samples (69%), and it was also the only term selected by more than 60% of consumers to describe the three samples (PBC1, PBC4, and PBC5) with the highest overall liking. The sample with the lowest overall liking, PBC3, was frequently described with "spice/herb", and "toasted/brown" which were subsequently identified as positive drivers of liking. Conversely, PBC2, which was also liked significantly less than the better-performing samples but more than PBC3, was mostly characterized (>50%) by negative terms such as "oily", "aftertaste", "greasy", and "tough". Consumers indicated that an ideal plant-based chicken product should have characteristics such as "meaty/savory", "chicken-like", "spice/herb", "toasted/brown", "crispy", "tender", and "moist/juicy".

Correspondence analysis (CA) was conducted on the CATA data to visualize the relationships between different plant-based chicken samples and their perceived sensory attributes; only the 24 significant attributes were included. Figure 2.2 shows the representation of the samples and terms in the first two coordinates of the CA performed on the frequency table using chi-square distances. Together, the first and second dimensions explained 92.57% of the total inertia, indicating that the first two dimensions provided a good representation of the

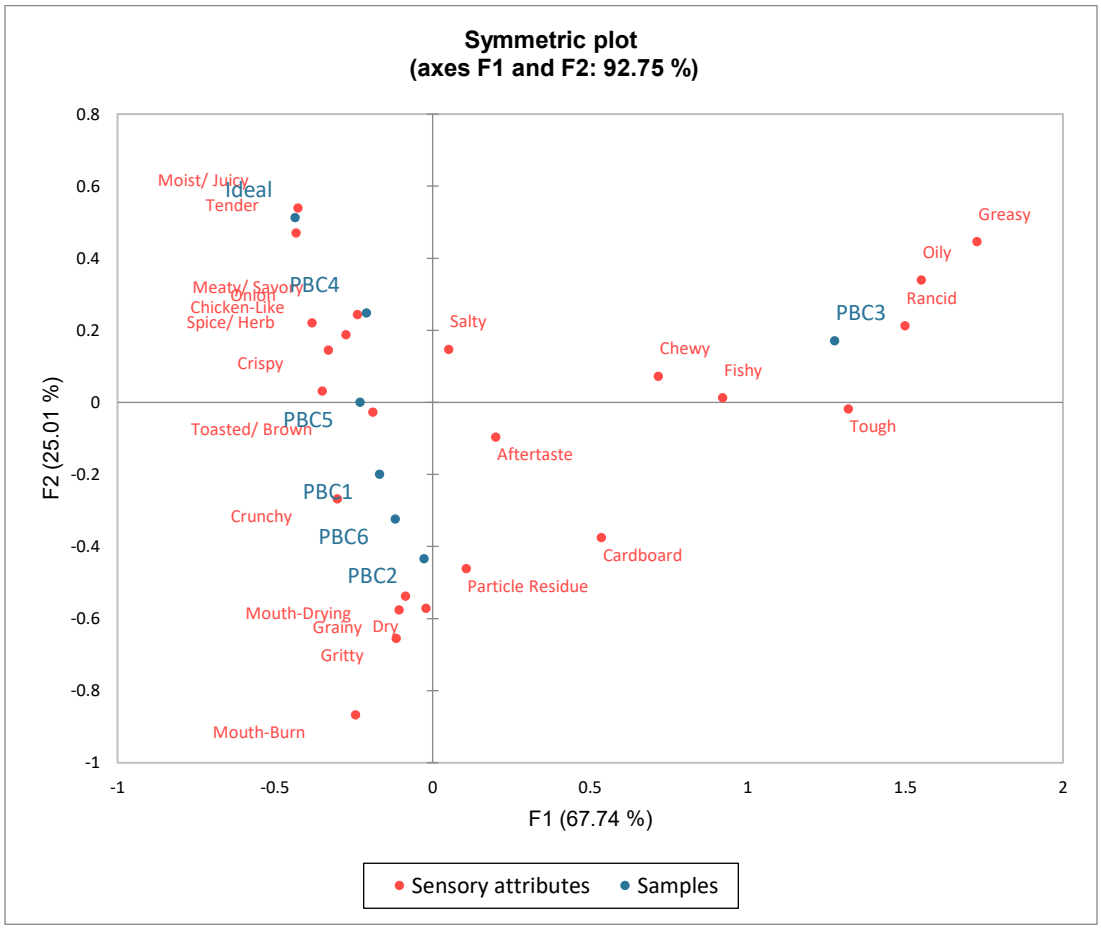
relationships between samples and sensory attributes. The distance between the points representing the samples indicates their similarity. Therefore, three groups of samples with similar sensory characteristics were identified: group 1 (PBC4 and PBC5), located on the negative axis of the first dimension and the positive/neutral axis of the second dimension; group 2 (PBC1, PBC2, and PBC6) located on the negative axis of the first dimension and negative axis of the second dimension; and lastly group 3 (PBC3), located on the positive axis of the first dimension. Among these three groups, the samples in group 1 were the closest to the ideal and received the highest overall liking, texture, flavor, and aftertaste liking scores (Table 2.3). The results of the CA were consistent with some of the patterns observed in the hedonic testing (Table 2.3), with a clear separation between the samples. Specifically, the first dimension clearly differentiated PBC3, which received the lowest liking rating on all measured indices, from the other samples. A significant p-value (0.0001) from the chi-square test indicated an association between the products and the CATA attributes. Hence, the ideal product, PBC4, and PBC5 were associated with attributes such as “moist/juicy”, “tender”, “meaty/savory”, “chicken-like”, “toasted/brown”, “onion”, and “crispy”, indicating that these attributes characterized the ideal product and the higher-liked PBC4 and PBC5 samples. The most disliked sample, PBC3, was positioned in the CA map in association with terms such as “tough”, “fishy”, “chewy”, “greasy”, and “rancid”.

Table 2.4: Frequency of CATA terms used to describe plant-based chicken samples by100 consumers

Attributes		PBC1	PBC2	PBC3	PBC4	PBC5	PBC6	Ideal
Flavor and Mouthfeel	Salty*	37^{ab}	41^{b}	31^{ab}	24^{a}	25^{ab}	33^{ab}	52
	Meaty/Savory*	50^{bcd}	26^{a}	55^{cd}	31^{ab}	60^{d}	39^{abc}	85
	Chicken-Like*	58^{bc}	22^{a}	55^{bc}	46^{bc}	63^{c}	40^{ab}	93
	Beany^{ns}	5^{a}	13^{a}	9^{a}	16^{a}	16^{a}	13^{a}	5
	Sweet^{ns}	4^{a}	2^{a}	5^{a}	4^{a}	2^{a}	2^{a}	5
	Soy^{ns}	14^{a}	20^{a}	15^{a}	15^{a}	23^{a}	11^{a}	3
	Sour^{ns}	2^{a}	7^{a}	1^{a}	1^{a}	2^{a}	2^{a}	3
	Oily*	8^{a}	78^{b}	5^{a}	4^{a}	6^{a}	7^{a}	6
	Grainy*	40^{bc}	11^{a}	27^{ab}	56^{c}	18^{a}	37^{b}	5
	Onion*	26^{bc}	4^{a}	37^{c}	9^{a}	30^{bc}	18^{ab}	35
	Spice/Herb*	47^{b}	13^{a}	60^{bc}	45^{b}	71^{c}	53^{bc}	85
	Cardboard*	26^{a}	47^{b}	15^{a}	46^{b}	10^{a}	18^{a}	2
	Fishy*	6^{a}	31^{b}	8^{a}	10^{a}	8^{a}	6^{a}	1
	Mouth-Burn*	2^{a}	0	3^{a}	3^{a}	0	10^{b}	0
	Green/Vegetable^{ns}	5^{a}	7^{a}	12^{a}	10^{a}	10^{a}	12^{a}	8
	Toasted/Brown*	81^{b}	36^{a}	80^{b}	70^{b}	67^{b}	77^{b}	87
	Rancid*	2^{a}	33^{b}	3^{a}	2^{a}	1^{a}	7^{a}	2
	Aftertaste*	37^{a}	59^{b}	44^{ab}	41^{ab}	39^{a}	54^{ab}	27
	Mouth-Drying*	33^{bc}	11^{a}	24^{abc}	37^{c}	20^{ab}	40^{c}	1
	Bitter^{ns}	7^{a}	13^{a}	6^{a}	5^{a}	4^{a}	10^{a}	1
	Particle Residue*	18^{ab}	15^{ab}	10^{a}	28^{b}	13^{ab}	24^{ab}	3
Texture	Chewy*	13^{a}	58^{b}	16^{a}	20^{a}	30^{a}	14^{a}	4
	Crispy*	56^{d}	8^{a}	51^{cd}	36^{bc}	29^{b}	45^{bcd}	70
	Tender*	21^{ab}	5^{a}	31^{b}	20^{ab}	57^{c}	19^{ab}	74
	Dry*	33^{bc}	14^{a}	22^{ab}	40^{c}	15^{a}	37^{bc}	1
	Firm^{ns}	21^{a}	20^{a}	27^{a}	30^{a}	24^{a}	21^{a}	10
	Crunchy*	64^{c}	6^{a}	53^{bc}	40^{b}	19^{a}	57^{bc}	38
	Moist/Juicy*	16^{ab}	6^{a}	30^{bc}	12^{a}	42^{c}	15^{ab}	66
	Greasy*	2^{a}	65^{b}	2^{a}	2^{a}	9^{a}	4^{a}	3
	Gritty*	12^{ab}	4^{a}	11^{ab}	24^{b}	8^{a}	24^{b}	1
	Tough*	10^{a}	58^{b}	7^{a}	16^{a}	1^{a}	7^{a}	1
	Toothpacking^{ns}	4^{a}	8^{a}	4^{a}	3^{a}	5^{a}	1^{a}	1

*Notes: ∗ Indicates significant differences among samples according to Cochran's Q test at $p < 0.05$, whereas **ns** indicates no significant differences ($p > 0.05$). The ideal product was not included in Cochran's Q test. Frequencies with different superscript letters within a row are significantly different according to the Sheskin procedure.*

Figure 2.2: Correspondence analysis biplot of Check-All-That-Apply (CATA) attributes and PBMAs



Identification of Drivers of Liking for Plant-Based Alternatives Using Penalty Analysis and Partial Least Squares Regression

To examine the impact of different attributes on liking, a penalty-lift analysis was conducted. Figure 2.3 presents a visual representation of attributes and their association with overall liking, based on the percentage of consumers who selected each attribute. Only attributes that were present for more than 20% of consumers (Plaehn, 2012) were considered. Therefore, the attributes in the upper-right quadrant are the most important for higher consumer acceptability, while those in the lower-right quadrant are associated with lower acceptance.

Although “Moist/juicy” was selected by approximately 20% of consumers, its selection was associated with an increase of approximately 2 points in overall liking. Figure 2.4 summarizes the results of the penalty-lift analysis identifying the attributes that are positively and negatively associated with overall liking. When consumers selected the terms “chicken-like”, “meaty/savory”, “tender”, “spice/herb”, “moist/juicy”, “toasted/brown”, “crispy”, “crunchy”, and “onion”, overall liking scores were higher than when those attributes were not selected. This suggests that these nine attributes were positively associated with overall liking. “Chicken-like” had the greatest positive mean difference in overall liking, with liking scores 2.7 points higher when the attribute was selected than when it was not selected, indicating it is an important positive driver of liking among the products evaluated. These findings align with previous studies on plant-based chicken, which identified attributes such as tenderness, juiciness, and meaty flavor, as well as chicken flavor, as drivers of liking (Collier et al., 2025; NECTAR, 2025; Godschalk-Broers, 2022). Additionally, crunchiness and crispiness have been identified as important attributes for consumer acceptance of chicken nuggets and other breaded chicken products (Cao et al., 2020). In contrast, the selection of terms such as “grainy”, “mouth-drying”, “chewy”, “dry”, “aftertaste”, and “cardboard” resulted in a penalty (negative) in overall liking scores, indicating that they were associated with lower overall liking. The presence of cardboard and aftertaste led to the highest penalties among the attributes meeting the 20% criterion, resulting in drops of 2.4 and 1.4, respectively, in overall liking means. The presence of an aftertaste is commonly associated with plant proteins, and this sensory attribute has consistently been reported as a driver of disliking for PBMAs across multiple studies (NECTAR, 2025; Ettinger et al., 2022). Ultimately, the results of the penalty-lift analysis reiterate the importance of textural and flavor attributes for the consumer acceptance of plant-based chicken pieces.

Partial Least Squares Regression (PLSR) was conducted on the significant CATA attributes and overall liking scores, using term frequencies as predictors and overall liking means as the response variable. Only attributes with Variable Importance in Projection (VIP) values > 1 (Figure 2.5) were considered main predictors in the model (Silva et al., 2025), whereas those with VIP values > 0.8 were considered moderately important predictors. The correlation loading plot (Figure 2.6) showed that higher liking was positively associated with the presence of attributes such as “meaty/savory”, “chicken-like”, “spice/herb”, “toasted/brown”, “crispy”, “tender”, “onion”, “moist/juicy”, and “crunchy”. Conversely, attributes such as “oily”, “cardboard”, “rancid”, “aftertaste”, “greasy”, “fishy”, “chewy”, and “tough” were negatively correlated with overall liking. Furthermore, regression coefficients indicate the direction and strength of the association between attribute frequency and liking. Significant standardized coefficients indicate that an attribute is a significant predictor of overall liking in the model. Hence, “tough”, “fishy”, and “cardboard” were significant negative predictors of liking (Figure 2.7), suggesting that texture and off flavors are primary barriers to consumer acceptance of PBMAs. Of the nine identified positive attributes associated with liking, only “crunchy” was a non-significant positive predictor.

A total of 15 drivers were obtained from penalty-lift analysis (9 positive and 6 negative), while 17 were identified via PLSR (9 positive and 8 negative), of which 11 were statistically significant (Figure 2.7). Eight attributes (“chicken-like”, “meaty/savory”, “tender”, “spice/herb”, “moist/juicy”, “toasted/brown”, “crispy”, and “cardboard”) were significant and consistent across both approaches, indicating their consistent association with liking or disliking across the two methods. Discrepancies among the remaining drivers can be attributed to the inherent differences between the two methods' analytical frameworks. Penalty-lift analysis is a univariate

approach that evaluates the individual association of each CATA attribute with overall liking, thereby ignoring inter-attribute correlations, which may result in attributes being identified as significant due to their correlation with other attributes (Table 2.5). In contrast, PLSR is a multivariate method that evaluates the entire sensory profile simultaneously and accounts for multicollinearity, which may explain why only a subset of attributes with VIP > 0.8 reached statistical significance. Nho et al. (2025) reported similar discrepancies in driver identification when comparing PLSR and penalty analysis.

Figure 2.3: Mean impact on overall liking as a function of the percentage of consumers who checked each attribute

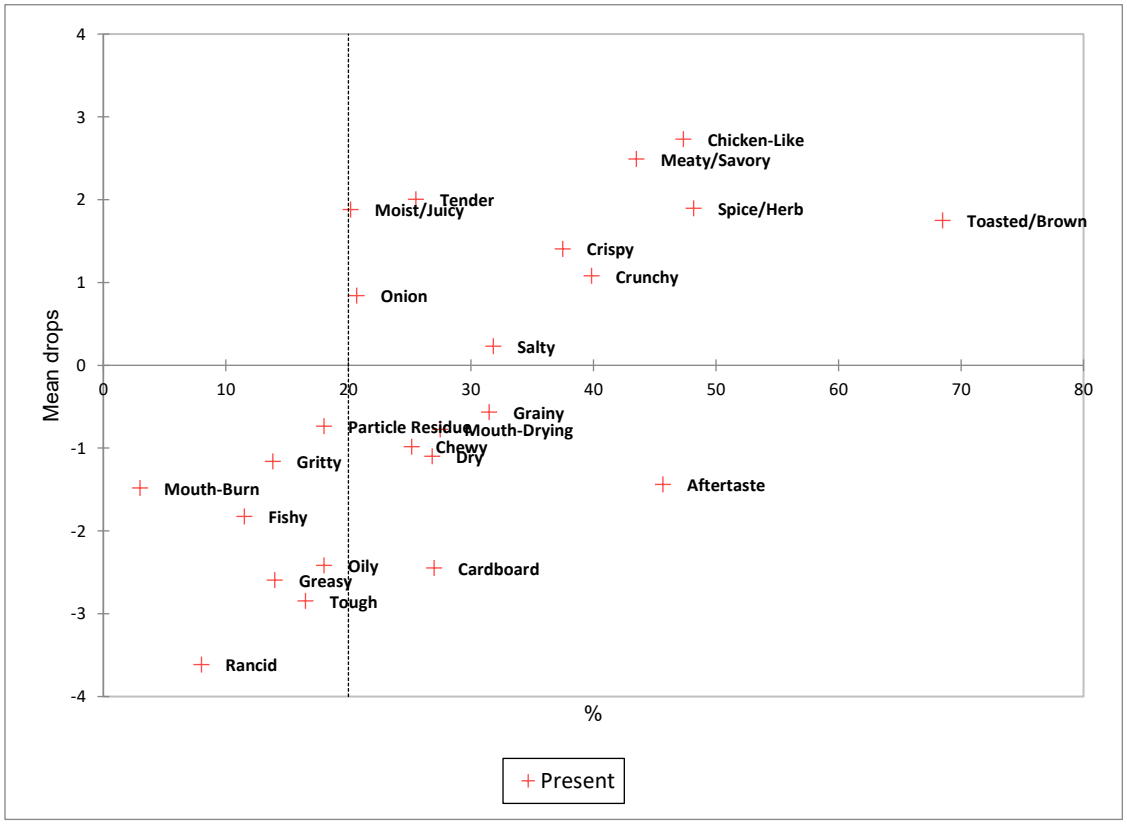


Figure 2.4: Penalty-Lift analysis associating hedonic scores and CATA (Check-All-That-Apply) data

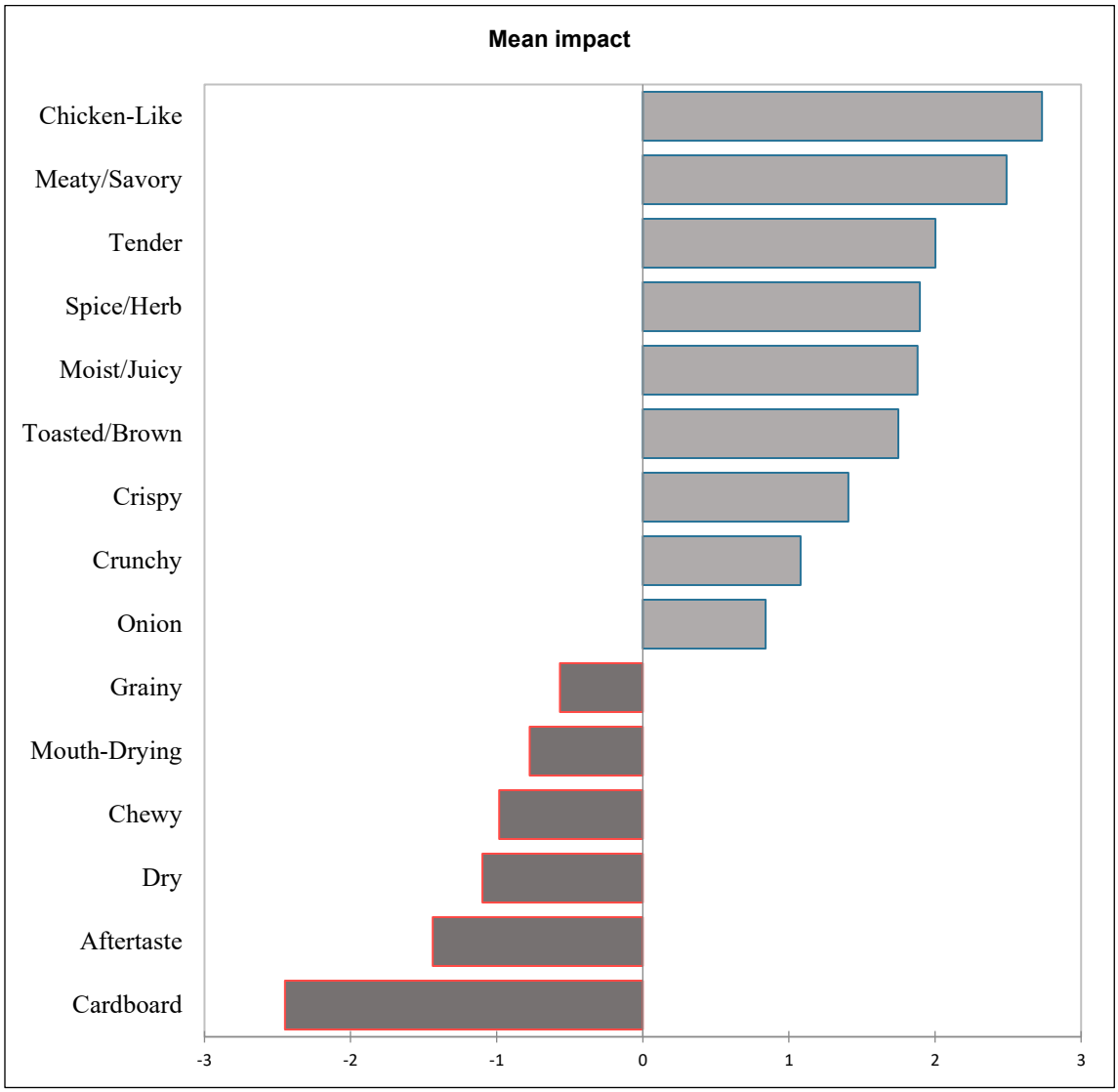
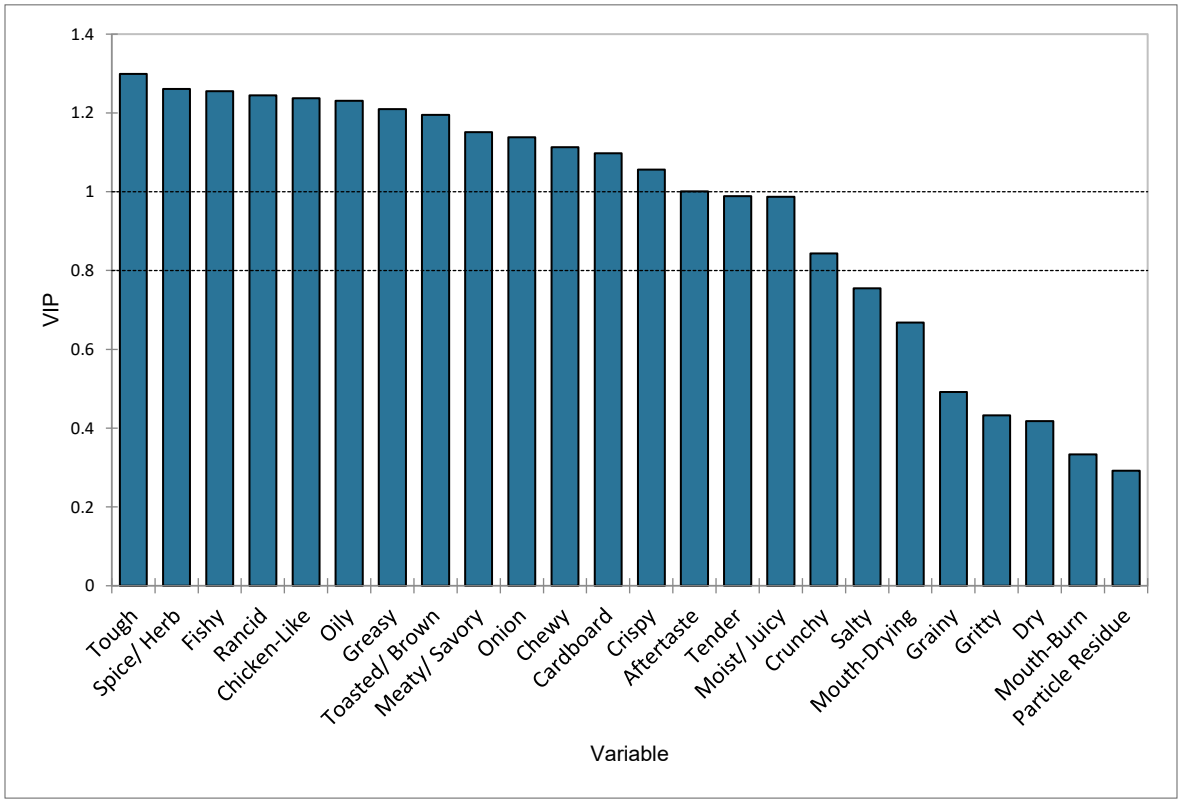


Table 2.5: Significant CATA attributes from penalty-lift analysis

Variable	Level	%	Mean impact	p-value	Significant
Meaty/Savory	Absent	56.50%			
	Present	43.50%	2.490	<0.0001	Yes
Chicken-Like	Absent	52.67%			
	Present	47.33%	2.732	<0.0001	Yes
Grainy	Absent	68.50%			
	Present	31.50%	-0.567	0.005	Yes
Onion	Absent	79.33%			
	Present	20.67%	0.841	0.000	Yes
Spice/Herb	Absent	51.83%			
	Present	48.17%	1.896	<0.0001	Yes
Cardboard	Absent	73.00%			
	Present	27.00%	-2.449	<0.0001	Yes
Toasted/Brown	Absent	31.50%			
	Present	68.50%	1.749	<0.0001	Yes
Aftertaste	Absent	54.33%			
	Present	45.67%	-1.438	<0.0001	Yes
Mouth-Drying	Absent	72.50%			
	Present	27.50%	-0.774	0.000	Yes
Chewy	Absent	74.83%			
	Present	25.17%	-0.983	<0.0001	Yes
Crispy	Absent	62.50%			
	Present	37.50%	1.407	<0.0001	Yes
Tender	Absent	74.50%			
	Present	25.50%	2.003	<0.0001	Yes
Dry	Absent	73.17%			
	Present	26.83%	-1.098	<0.0001	Yes
Crunchy	Absent	60.17%			
	Present	39.83%	1.080	<0.0001	Yes
Moist/Juicy	Absent	79.83%			
	Present	20.17%	1.881	<0.0001	Yes

Figure 2.5: Variable Importance in Projection (VIP) scores from PLSR analysis



**Attributes with VIP scores between 0.8 and 1 are moderately important predictors in the model, while those with scores > 1 are the main predictors*

Figure 2.6: Correlation loading plot from PLSR analysis

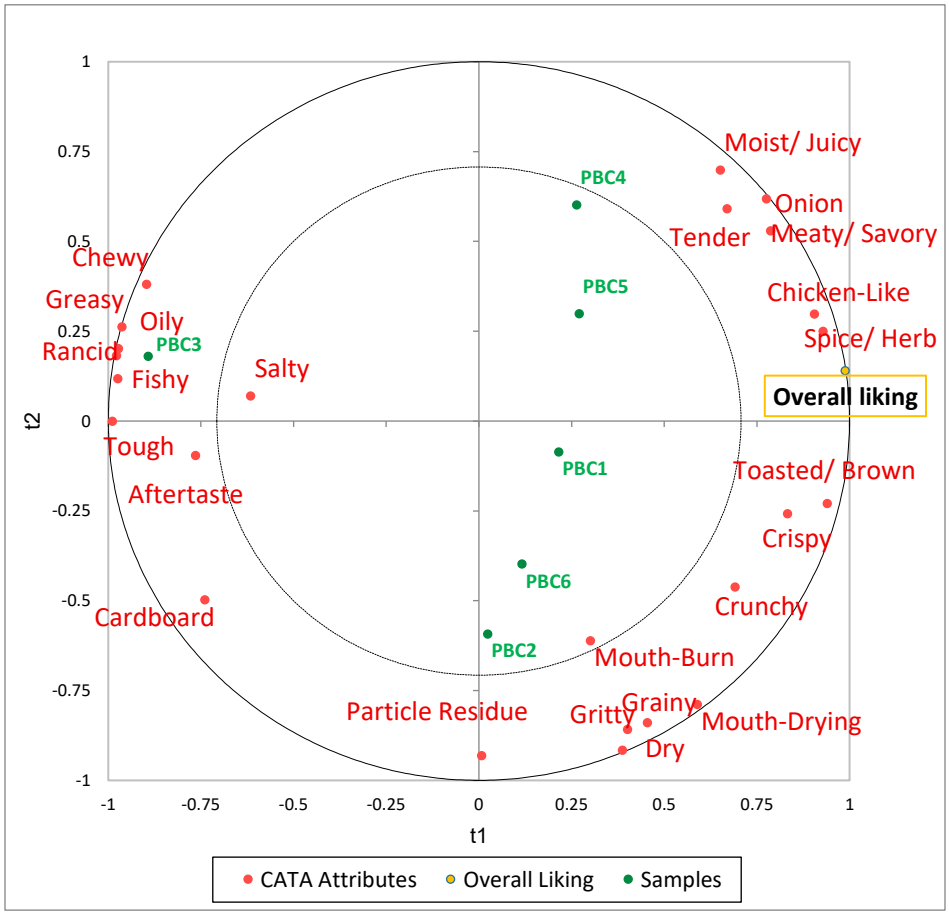
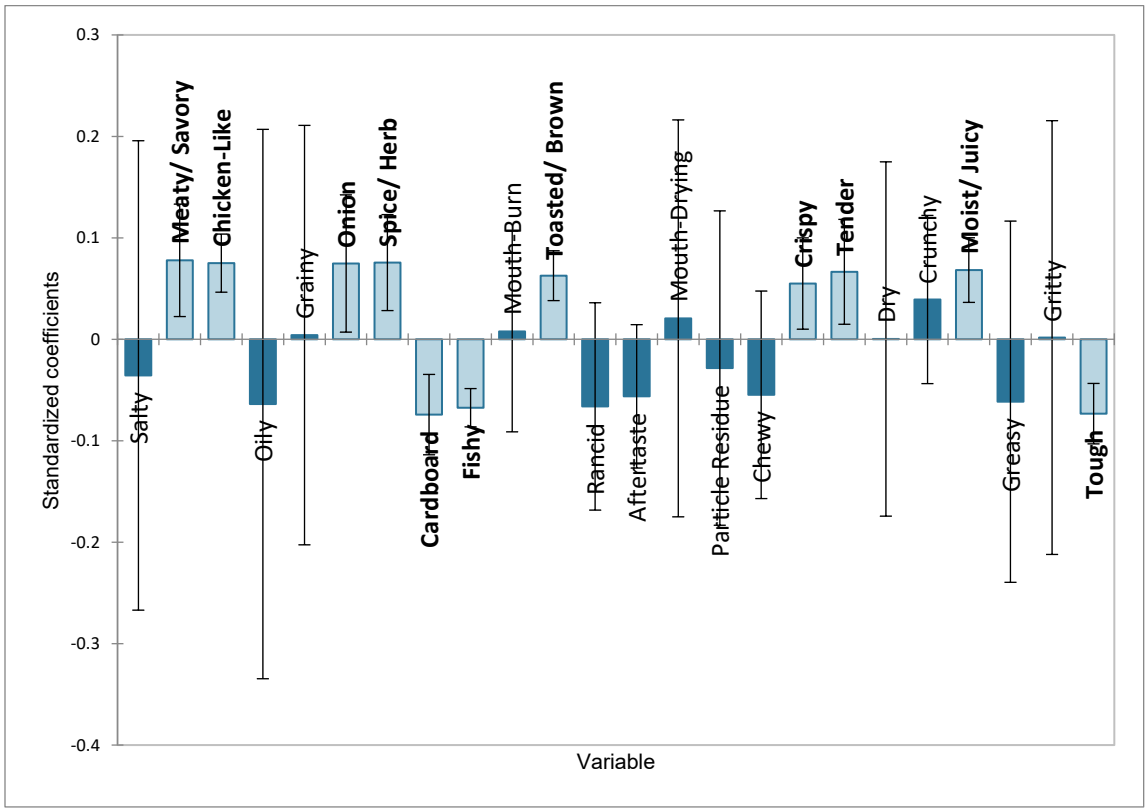


Figure 2.7: Standardized coefficients for sensory drivers of overall liking based on the PLSR model.



**Attributes in bold with light blue bars indicate significant coefficients based on 95% confidence intervals among those with VIP scores > 0.8*

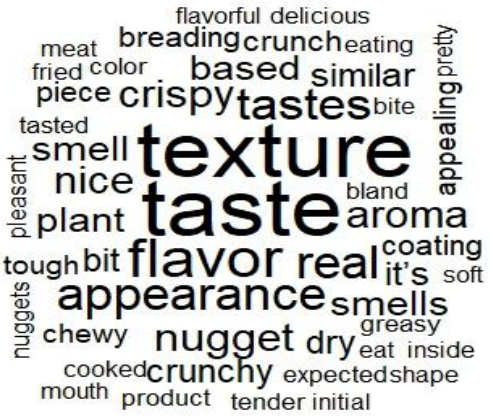
Open-Ended Comments

Before answering the CATA questions, participants were asked to provide an e-commerce-style review of the sensory properties of the plant-based chicken pieces. This was to provide insights into how consumers typically describe samples sensorially, and to assess whether the CATA terms reflected consumers' language. The open-ended comments were examined by means of a word cloud created in R and displayed in Figure 2.8. The word cloud in Figure 2.8A was generated from comments from each consumer's first evaluation, before they were introduced to the CATA list. It can be observed that frequently mentioned terms, including texture, taste, flavor, appearance, and aroma, were general modalities on which they had

answered hedonic questions prior to the open-ended question. Aside from these, more descriptive terms, such as tender, tough, chewy, crunchy, greasy, dry, and crispy, which were included in the CATA questions, were mentioned. Figure 2.8B additionally shows the word cloud generated from open-ended comments for subsequent evaluations, after consumers had already answered a CATA question. A few of the terms in the CATA list that were not mentioned previously, such as aftertaste, onion, juicy, and oily, showed up, indicating that participants may have relied on the CATA questions to broaden their vocabulary. Nonetheless, these results support the relevance of several of the CATA terms to consumers' descriptions of the products, although consumers may often have limited sensory vocabulary.

Figure 2.8: Word cloud from open-ended comments separated by product position

A) 1st position



B) 2nd to 6th position

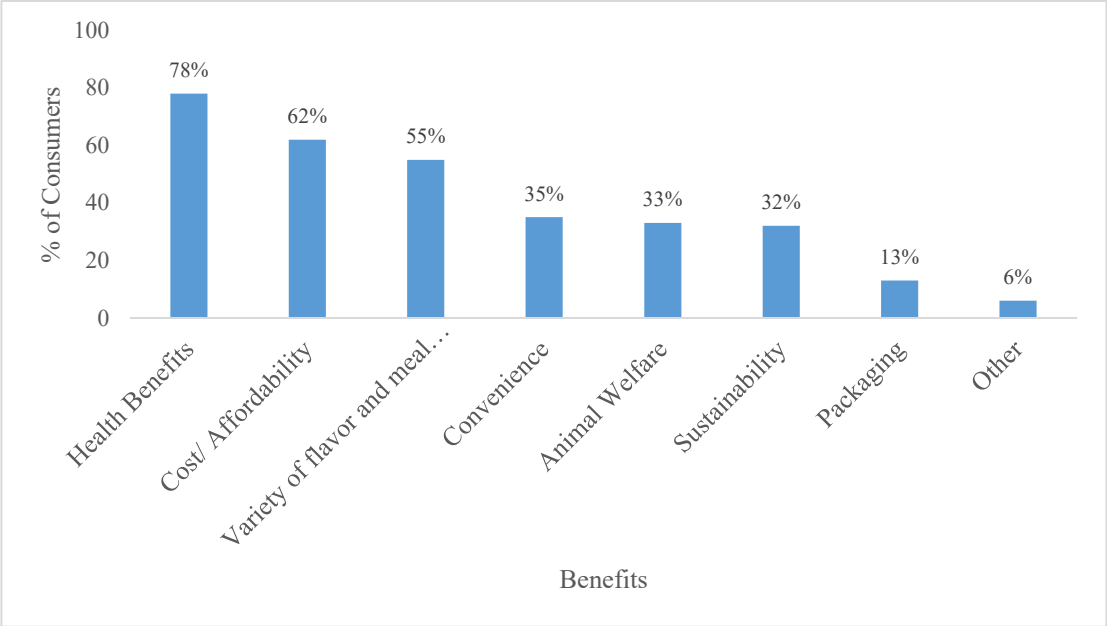


Consumer Motivations and Barriers to Purchase

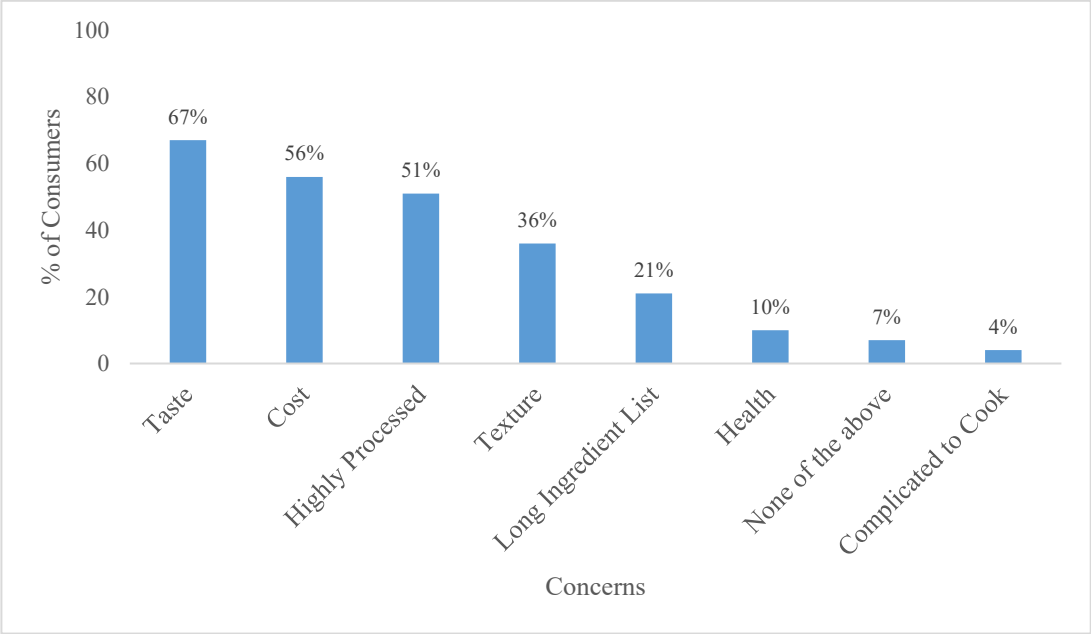
At the end of the evaluation, consumers were asked CATA questions about the perceived benefits of PBMAs that would encourage them to try new products, as well as their concerns about PBMAs (Figure 2.9). For the benefits of PBMAs, “Health benefits”, “Cost/Affordability”, and “Variety of Meal and flavor options” (Figure 2.9A) were selected more than 50% of the time. Health benefits, being the most selected, may be attributable to growing health-consciousness among consumers, where they are seeking meals that are lower in calories and cholesterol, while others are seeking to reduce their red meat consumption due to health risks, associated with frequent consumption. Likewise, in terms of cost/affordability, consumers are willing to try new PBMAs if they are more affordable, possibly compared to their animal-based counterparts. It is noteworthy that only 9% of consumers in this study were non-meat-eaters (vegans and vegetarians), which may explain why “Variety of Meal and Flavor options” was also frequently selected. This suggests that meat-eaters may also be interested in incorporating PBMAs into their meals for greater variety. Additionally, other factors such as “Convenience”, “Animal Welfare”, and “Sustainability”, while they may influence consumer purchasing decisions, were less frequently selected as reasons for trying new PBMAs in this study. When consumers were asked about their concerns regarding PBMAs, “taste” was the top choice (Figure 2.9B), ahead of other reasons such as “cost” and “highly processed”. This further reiterates that taste and sensory properties of PBMAs are important barriers to their acceptance. Cost is also a top concern, which is not surprising, as most PBMAs tend to be more expensive than their animal-based counterpart for the same quantity of products. Consumers were less concerned about long ingredient lists, with this option selected by 21% of participants.

Figure 2.9: Consumer Perceptions about PBMAs based on Check-all-that-apply responses

A) Benefits



B) Concerns



Conclusion

In this study, six different plant-based chicken products including nuggets, tenders, and pieces were evaluated. Products containing pea protein were among those with higher consumer acceptance; however, because the commercial products differed in multiple formulation and processing characteristics, these differences cannot be attributed specifically to protein sources. Additionally, the sensory drivers of liking for plant-based chicken were examined using CATA-derived data through penalty-lift analysis and PLSR. The attributes common to both techniques showed consistent associations with liking and disliking of plant-based chicken. Therefore, the presence of sensory attributes such as “meaty/savory”, “chicken-like”, “spice/herb”, “toasted/brown”, “crispy”, “tender”, and “moist/juicy” was associated with higher consumer acceptance of the PBMAs evaluated. These attributes were also among those desired by consumers in an ideal product. On the other hand, the undesirable “cardboard” flavor attribute was consistently associated with lower product appeal.

Future research should expand to include a larger group of non-meat eaters, specifically vegans and vegetarians. Such studies could help determine whether a “chicken-like” flavor note remains an important positive driver of liking among consumers who do not consume meat.

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Chapter 3 - AI Analysis of E-Commerce Reviews to Identify Drivers of Liking of Plant-Based Meat Analysis

Abstract

Online product reviews provide a valuable source of unprompted consumer feedback that may offer insight into sensory drivers of liking. However, extracting meaningful sensory information from these reviews remains challenging because review text is unstructured and varies in detail. This chapter explored ChatGPT as an AI tool for identifying drivers of liking and disliking in e-commerce reviews of plant-based chicken products. 631 Publicly available Amazon reviews for six plant-based chicken products were collected and cleaned to retain only sensory-relevant comments, resulting in 182 reviews for analysis. Three AI-based approaches were used: AI-inferred formulation-based analysis using ingredient lists, qualitative analysis of cleaned review text, and quantitative analysis combining attribute mentions with star ratings using Partial Least Squares Regression. Based solely on the formulation, ChatGPT predicted that desirable attributes such as “juicy,” “moist,” “savory,” “seasoned,” “cohesive,” “onion,” “brothy,” and “toasted” may be associated with liking. In contrast, “dry,” “rubbery,” “oily,” “flat,” “green,” “artificial,” “crumbly,” “pasty,” “beany,” and “spongy” were predicted to be associated with disliking. Qualitative review text analysis identified positive drivers such as “juicy”, “moist”, “crispy”, “crunchy”, “soft”, “firm”, “savory”, “seasoned”, and “salty” while attributes like “dry”, “chewy”, “rubbery”, “tough”, “greasy”, “oily”, “bland”, and “spongy” were associated with negative perceptions. Quantitative analysis of reviews and ratings reinforced these patterns with one exception: “crunchy,” “juicy,” “crispy,” and “fishy” were positively associated with higher ratings, while “rubbery,” “tough,” and “salty” were significant predictors of lower ratings. Although the positive association of “fishy” with higher overall ratings contradicted expectations

for plant-based meat alternatives, most findings aligned with previous sensory research showing that texture remains a major factor associated with consumer acceptance. Overall, this research suggests that AI-assisted analysis of online reviews can provide a rapid, useful approach to extracting sensory insights from unstructured consumer feedback. However, because online reviews are uncontrolled and vary in detail, researchers should compare these findings with those obtained using conventional sensory methods before using them for product optimization.

Introduction

Online reviews are a form of user-generated content that provides qualitative evaluations of a consumer's experience with a product or service (Kim et al., 2024). They serve as a digital record of post-purchase satisfaction, captured across e-commerce platforms and other online platforms. As a result, they provide a valuable source of unprompted consumer data, enabling researchers to analyze consumer feedback throughout the product's market history without additional data collection (Espinosa-Ramos et al., 2025). Consumers generally review products based on sensory experience (touch, smell, sight, hearing, and taste) or practical properties, such as performance, features, and the installation/set-up process (Lopez & Garza, 2022). The former explains the growing interest in using online reviews to obtain sensory insights.

In sensory science, online reviews share similarities with free-comment methods used in Central Location Tests (CLT) or Home-Use Tests (HUT), as both provide consumer-generated descriptions of product experiences. While traditional methods require rigorous recruitment, questionnaire design, and participant incentives, e-commerce data offer large, unsolicited, and readily accessible sources of consumer feedback. Compared with conventional sensory methodologies, these reviews can provide feedback from a larger number of consumers and reflect product experiences under real-world consumption conditions that are not captured in controlled testing settings.

The challenge, however, is that the unstructured nature and sheer volume of review data make manual human processing time-consuming and challenging (Agnihotri & Bhattacharya, 2016; Hou et al., 2019). Consequently, specialized computational approaches can be used to translate these data into actionable insights. Extracting sensory information from review text typically follows a data-processing pipeline similar to those used in free-text analysis in sensory

science, including data scraping, text cleaning, lemmatization, and synonymization to identify core sensory attributes (Hamilton & Lahne, 2020). To execute this at scale, computational methods such as Natural Language Processing (NLP) and text mining are increasingly employed, as they can convert unstructured text into structured information for subsequent analysis (Jain & Pamula, 2020). Consequently, these approaches have been used in the literature to extract sensory information such as descriptors, emotions, sentiments, and drivers of liking from consumer texts to better understand consumer behavior toward different products and predict consumer preference. Notable among such studies are those on coffee (Espinosa-Ramos et al., 2025), whisky (Hamilton & Lahne, 2020; Hamilton et al., 2023), and chocolate (Mahieu et al., 2020). Collectively, these studies highlight the potential of NLP-based frameworks to translate unstructured consumer text into structured sensory information.

Despite their usefulness, current NLP tools for lexicon development and data cleaning to analyze sensory insights from consumer text still require several time-consuming manual steps to ensure that extracted attributes are used strictly in a sensory context (Chen et al., 2021; Espinosa-Ramos et al., 2025). Large Language Models (LLMs) may provide an alternative approach; as advanced AI systems trained on large natural language datasets, LLMs can generate human-like text responses (Lee et al., 2025). This framework enables them to handle a broad range of language-based tasks, including translation, text summarization, and content generation, with minimal human supervision (Motoki et al., 2025). Notable examples of LLMs include ChatGPT, PaLM, Llama, Gemini, and Claude. Recent studies show that ChatGPT is a promising tool for text analysis (Rathje et al., 2024). Additionally, Torrico (2025) demonstrated ChatGPT's potential to predict sensory characteristics of hypothetical chocolate brownie formulations. The

study showed that ChatGPT could generate sensory descriptions and quality scores for different hypothetical formulations, suggesting potential applications for supporting product development.

Therefore, this study aimed to examine ChatGPT's potential to identify AI-inferred formulation-based, qualitative review-based, and quantitative review-based drivers of liking of plant-based meat alternatives using product formulation information and consumer reviews publicly available on Amazon, an e-commerce platform.

Materials and Method

Online Review Selection and Scraping

The category of plant-based chicken products was selected based on the availability of at least six products, each with at least 50 reviews from verified purchasers on Amazon. To ensure data integrity, reviews from manufacturer websites were excluded to avoid potential promotional bias. Platforms such as Walmart and Target were initially considered but were ultimately omitted due to web-scraping restrictions. To systematically collect review text, star ratings, and usernames for subsequent analysis, Octoparse, a no-code web scraping tool, was used to extract a total of 631 publicly available Amazon reviews dating from February 2020 to January 2026.

Data Cleaning and Processing

Prompt engineering was used to preprocess reviews and subsequently extract sensory information. Text cleaning was performed using ChatGPT (GPT-5.2) on January 20, 2026, to refine the review dataset, which was organized into three columns: product name (PBC1 to PBC6), star rating, and review text. The cleaning process involved two specific instructions. Prompt 1: *"Clean up this file like how tidytext in R would. Maintain the ratings and product name columns. For the written reviews, remove emojis, images, or any review that does not*

describe the sensory properties of the plant-based chicken products. Treat each row as one data point. Create an Excel file with the cleaned reviews afterward." While this initial step reduced the dataset to 585 reviews from an initial 631 reviews and eliminated non-text characters, a manual check revealed that many reviews without sensory terms remained. To address this, Prompt 2 was issued: "*Remove any review that does not contain a sensory term*." This final filtration narrowed the dataset to 196 sensory-relevant reviews for further analysis. Each prompt was issued once.

Following the cleaning phase, ChatGPT (GPT-5.2**)** was used in three chat sessions to conduct specialized analyses. To identify AI-inferred drivers of liking based on formulation, a comprehensive list of ingredients shown on product packaging for all six products was compiled. These data were then presented to the model, along with a prompt asking it to predict the potential sensory drivers of liking and disliking for the product category based specifically on the ingredient profiles. Main Prompt: "Act *as an experienced taster and a trained sensory panelist. The following text provides the ingredient lists for 6 commercially available plant-based chicken products. Based on the ingredients list, determine the drivers of sensory liking or disliking for the product category. Your drivers should not be hedonic; they should be singular and unambiguous and should focus on only the sensory notes*". The initial prompt generated a series of multi-word descriptors; consequently, a follow-up instruction "*regenerate the list of drivers, and provide single-word descriptors only*" was issued to refine these outputs into concise, single-word drivers.

The second chat session aimed to identify qualitative drivers of liking from the review text. The input dataset for this stage was restricted to the cleaned reviews, containing only the product names and the corresponding review content. Prompt: "*Based solely on the text reviews*

provided, identify the sensory drivers of liking of plant-based chicken as a category. Drivers should strictly be single-word descriptive sensory terms; they should not be hedonic or ambiguous". The initial output included descriptors such as "breaded" and "fried". To further examine the reasoning behind their inclusion, the follow-up question "*are fried and breaded also drivers of liking*?" was asked. The discussion then considered whether these terms represented sensory perceptions or instead reflected product format or preparation, which led to their exclusion. Additional follow-up questions focused on the inclusion of "tender", particularly because some of the products in the dataset were chicken tenders, including "*did you include tender because it was mentioned? I am asking because some of the reviewed products include chicken tenders*." These questions prompted further clarification of *the* distinction between "tender" as a texture descriptor and tender as a product-form term. The initial list was subsequently re-evaluated by the model, to remove terms that were ambiguous, hedonic, or related to product format or preparation rather than direct sensory perception. The final drivers of liking and disliking were then recorded based on the refined interpretation of the review text.

The third chat session used a quantitative approach to extract sensory terms from the cleaned reviews and convert them into a binary Check-All-That-Apply (CATA) format: 1 indicated that a sensory term had been mentioned in a review, and 0 indicated that it was not mentioned. This conversion facilitated subsequent statistical analysis to identify attributes associated with liking based on consumer star ratings. Prompt: "*Using the provided text, generate a binary table, CATA-style data, where sensory attributes are either present or absent based on being mentioned and how they are used in the review. Treat each row as a single consumer and maintain the associated ratings and product name. Sensory attributes should be purely descriptive, non-hedonic, and unambiguous single words. Produce results in a*

downloadable Excel file." The resulting binary output consisting of 33 attributes (columns) and 196 rows (reviews) was manually inspected to ensure accuracy. Six reviews (rows) were removed because they did not mention any of the identified attributes, leaving a sample of 190 reviews that mentioned at least one of the 33 generated attributes. Additionally, frequent terms such as "cardboard" and implied "chicken-like" attributes were found to have been overlooked; consequently, an additional instruction "*create a new file and include chicken-like and cardboard in the list of terms, and check for their mentions in the reviews*" was given to include these attributes which had already been mentioned by reviewers in the retained sensory-related reviews in the AI-generated binary dataset bringing the number of attributes to 35. The detection of "chicken-like" was subsequently refined to capture expressions such as "like chicken" and "tastes like chicken". Another inspection of the dataset revealed that cooking-related terms such as "grilled", "baked", and "fried" were included; however, in the reviews, they were often used to describe how consumers prepared the products, and therefore those term columns were manually removed from the binary dataset, which brought the total attribute list to 32 from 35. A final manual check was performed on the attribute "tender" in the retained reviews to resolve potential naming ambiguity, as chicken tenders were included in the products under consideration, and each mention was verified to ensure it was used as a sensory descriptor rather than just a reference to the product name. The manual checks, attribute addition and removal brought the final dataset to 182 rows from 190 each representing a single review.

Data Analysis

Differences in ratings across products were assessed using the Kruskal–Wallis test due to unequal numbers of reviews. Pearson's chi-squared test was used to determine whether the frequency of mention of each sensory attribute differed significantly among products.

Correspondence analysis was performed on a contingency table with products in rows and mentioned terms in columns, using chi-squared distances, to generate a sensory map visualizing relationships between the samples and the descriptors.

Partial least squares regression (PLSR) analysis was performed on the final binary dataset consisting of 182 review mentions and ratings to identify drivers of liking. The frequency of binary attribute mentions (0 = not mentioned; 1 = mentioned) was treated as predictors, and the corresponding star rating for each review was treated as the response variable. Attributes with variable importance for projection (VIP) scores > 0.8 and significant standardized coefficients were interpreted as drivers of liking and disliking. All statistical analyses were conducted in XLSTAT (Addinsoft, New York, USA).

Results and Discussion

Consumer Star Ratings of Plant-based Chicken Products

A Kruskal-Wallis test was conducted to compare consumer star ratings across the six plant-based chicken products (N = 182). The results indicated no statistically significant differences in ratings between the products (p-value = 0.059). Although the overall test was not statistically significant, PBC6 and PBC2 had the highest mean ranks, while PBC3 had the lowest (Table 3.1).

Table 3.1: Summary of reviews by product and Kruskal-Wallis analysis

Product	Extracted Reviews	Retained Reviews	Mean Rating	Mean Rank
PBC1	162	27	4.19	100.72
PBC2	100	37	4.43	103.59
PBC3	99	43	3.53	77.28
PBC4	90	23	4.00	93.65
PBC5	100	36	3.64	81.96
PBC6	80	16	4.38	104.56

AI-Extracted Attributes

ChatGPT extracted 32 sensory attributes and organized them into a binary matrix indicating their presence or absence in each review. The final list included the following descriptors: “brown”, “buttery”, “cardboard”, “chewy”, “chicken-like”, “crispy”, “crunchy”, “dry”, “firm”, “fishy”, “flaky”, “golden”, “grainy”, “greasy”, “hard”, “juicy”, “moist”, “mushy”, “nutty”, “oily”, “pungent”, “roasted”, “rubbery”, “salty”, “soft”, “spicy”, “sweet”, “tender”, “thick”, “thin”, “toasted”, and “tough”. Each attribute was mentioned at least once across the 182 retained reviews.

A manual inspection of all extracted reviews showed that reviewers often described sensory dimensions in general terms, mentioning overall flavor, texture, aroma, and appearance, while others provided purely hedonic feedback, which contributed to the significant reduction in the dataset, with only one-third of reviews retained. By prioritizing descriptive, non-hedonic, and unambiguous singular terms, the extraction process focused exclusively on specific sensory attributes which had been mentioned in the reviews. Table 3.2 presents the twelve most frequently mentioned attributes; Pearson chi-squared analysis showed that the frequency of mentions for "chicken-like," "chewy," "crispy," "crunchy," "rubbery," and "thick" differed significantly among products ($p < 0.05$).

Additionally, correspondence analysis was conducted on the 12 most frequently mentioned terms to visualize the relationship between the products and the AI-extracted terms using chi-square distances (Figure 3.1). The first and second dimensions accounted for 82.60% of the total inertia. Based on the symmetric plot of CA, Samples PBC1, PBC2, and PBC6 occupied the same region together in the lower-left quadrant and were primarily associated with the terms “crispy”, “tender,” and “chicken-like”. The other samples were not close to each other

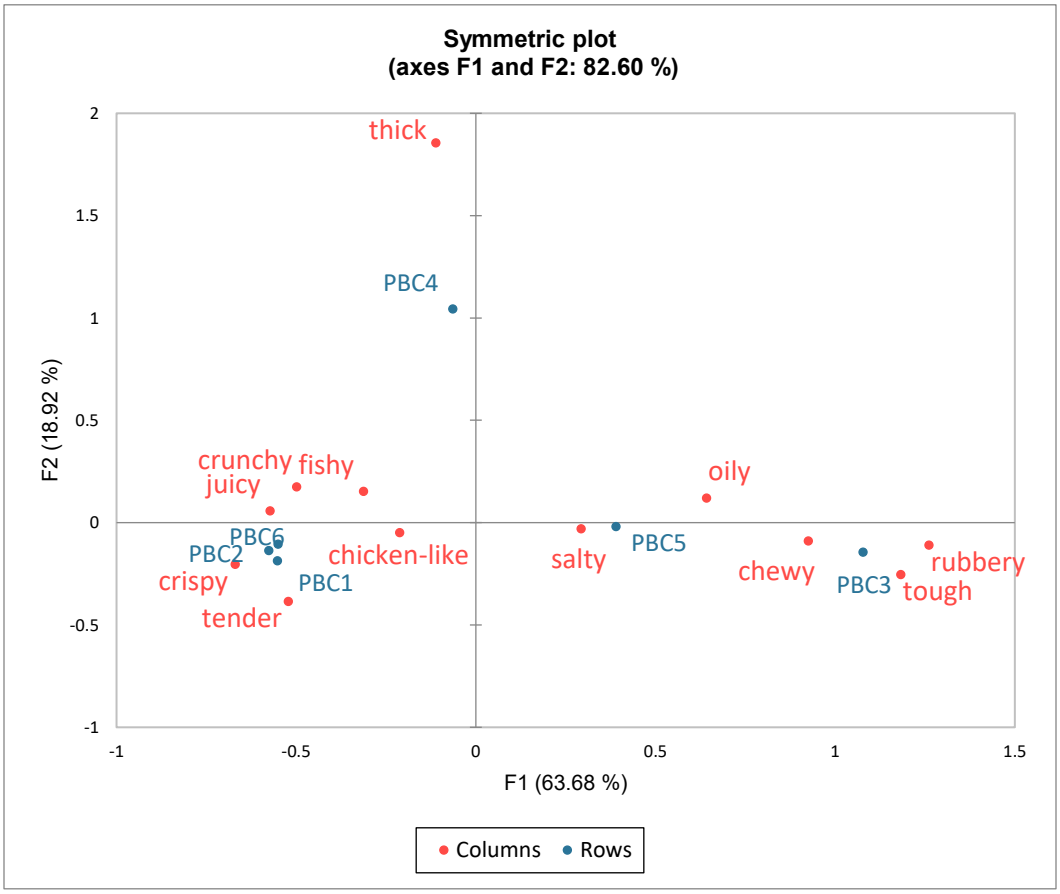
and were associated with different terms: PBC5 with “salty” and “oily”, PBC4 with “thick”, and PBC3 with “chewy”, “rubbery”, and “tough”. The first dimension was largely defined by textural attributes, separating the products associated with “crispy” and “tender” on the left from those associated with “chewy”, “rubbery”, and “tough” on the right. The Pearson chi-square and correspondence analyses showed differences in sensory terms mentioned in online reviews across the PBMAs evaluated.

Table 3.2: Frequency of the 12 most common sensory attributes in the online review dataset

	Attribute	**PBC1**	**PBC2**	**PBC3**	**PBC4**	**PBC5**	**PBC6**	**Pearson Chi-square (p-value)**
1	Chicken-like*	8	6	3	3	10	8	0.005
2	Chewy*	0	2	8	1	3	0	0.039
3	Crispy*	8	19	1	2	2	5	<0.0001
4	Crunchy*	6	6	1	4	2	5	0.019
5	Oily	1	2	10	3	3	1	0.111
6	Rubbery*	0	0	11	1	4	0	0.007
7	Salty	3	0	3	1	3	1	0.528
8	Tender	4	4	1	0	1	2	0.110
9	Juicy	2	2	0	1	1	2	0.372
10	Tough	0	0	4	0	3	0	0.078
11	Fishy	1	2	1	1	0	1	0.835
12	Thick*	0	1	0	4	1	0	0.004

**Indicates a significant attribute from the Pearson Chi-squared test ($p<0.05$)*

Figure 3.1: Correspondence analysis biplot of online review dataset



AI-Assessment of Drivers of Liking and Disliking

Three distinct approaches were employed to identify drivers of liking using ChatGPT (GPT-5.2). The first approach identified AI-inferred, formulation-based drivers from ingredient information. When given the ingredient lists for each of the six products, ChatGPT inferred "fibrous," "juicy," "savory," "brothy," "toasted," "allium/onion," "moist," and "cohesive" as drivers of potential liking, while "rubbery," "gummy," "crumbly," "chalky," "pasty," "dry," "beany," "green," "artificial," and "flat" were inferred as potential drivers of disliking (Table 3.3). The model indicated that these drivers were predicted from anticipated sensory relationships among ingredients across the six plant-based chicken formulations. Wheat gluten, textured wheat protein, protein concentrates, methylcellulose, starches, water, and oils were

predicted to be associated with fibrous, cohesive, juicy, and moist characteristics. In contrast, yeast extract, natural flavors, spices, onion, and garlic were predicted to be associated with savory, brothy, toasted, and allium/onion notes. Gluten and methylcellulose were considered potential contributors to rubbery and gummy textures; protein ingredients to crumbly, chalky, dry, beany, and green characteristics; starches to a pasty texture; and flavoring systems to artificial and flat notes.

In the second chat session, ChatGPT was provided with extracted and cleaned review text and asked to identify the sensory drivers based on the context in which the attributes were mentioned: “juicy”, “moist”, “crispy”, “crunchy”, “soft”, “firm”, “savory”, “seasoned”, and “salty” were identified as drivers of liking, while “dry”, “chewy”, “rubbery”, “tough”, “greasy”, “oily”, “bland”, and “spongy” were the identified as drivers of disliking. The model explained that this output was based on the context in which these terms appeared in reviews and how they related to expressions of overall product satisfaction or dissatisfaction.

Finally, the study used a quantitative approach, applying Partial Least Squares Regression to model the relationship between attribute mentions and reviewer star ratings. Attributes with VIP scores greater than 1.0 were considered important predictors of reviewer start ratings, while those greater than 0.8 were considered moderately important predictors (Figure 3.2). The correlation loading plot (Figure 3.3) indicated that “crunchy,” “juicy,” “crispy,” and “fishy” were positively associated with higher ratings. Conversely, attributes such as “chewy,” “tough,” “rubbery,” and “oily” were associated with lower reviewer star ratings and were also associated with PBC3 in the correlation loading plot. Among the negative predictors, “rubbery,” “tough,” and “salty” were statistically significant in the model (Figure 3.4). Among the positive predictors, “crunchy,” “juicy,” “crispy,” and “fishy” were statistically significant.

Although fishy flavor is generally considered undesirable in plant-based meat alternatives, its positive association with higher ratings was inconsistent with previous findings in the literature. Nevertheless, most identified drivers were consistent with previous findings from controlled sensory testing, which have shown that textural defects can be important barriers to consumer acceptance of plant-based meat alternatives, while juiciness is desirable (Godschalk-Broers & Scholten, 2022).

Overall, the three approaches identified different numbers of drivers: AI-inferred formulation-based (18), qualitative (17), and quantitative (7), with "juicy" and "rubbery" as the only drivers consistent across all three. Six drivers identified in the quantitative approach (crunchy, juicy, crispy, salty, tough, rubbery) were also identified in the qualitative approach, and the direction of their association with liking was consistent between the two approaches, except for "salty," which was predicted as a positive driver of liking by ChatGPT based on the review text, but was found to be a negative driver in the PLSR analysis. The reduced number of drivers identified in the quantitative approach may be attributable to the relatively low frequency of attribute mentions and the limited number of reviews retained for analysis.

Figure 3.2: Variable Importance in Projection (VIP) scores from PLSR

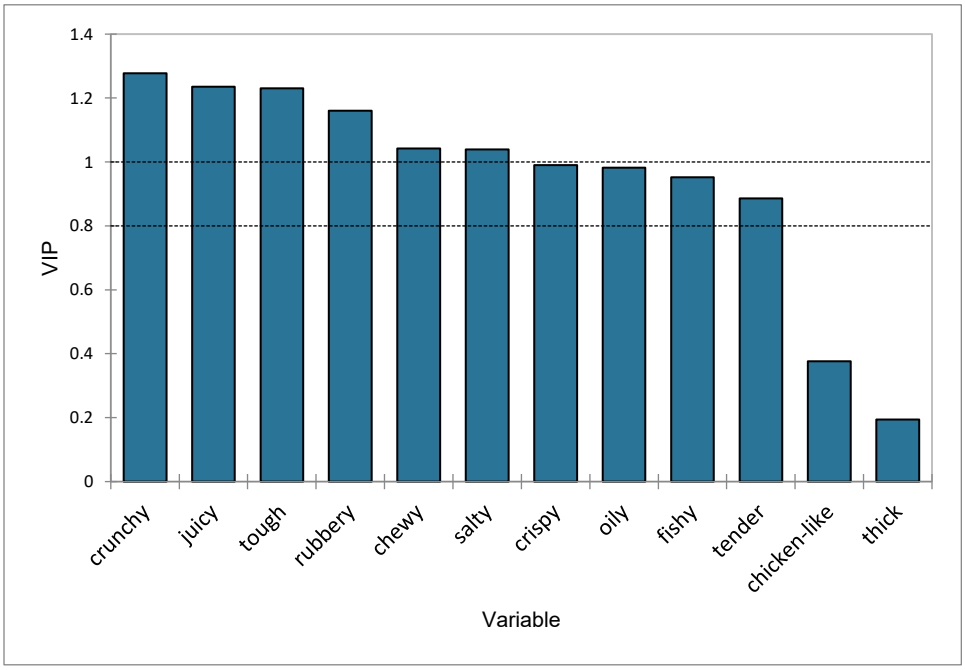


Figure 3.3: Correlation loading plot from PLSR analysis of star ratings and review mentions

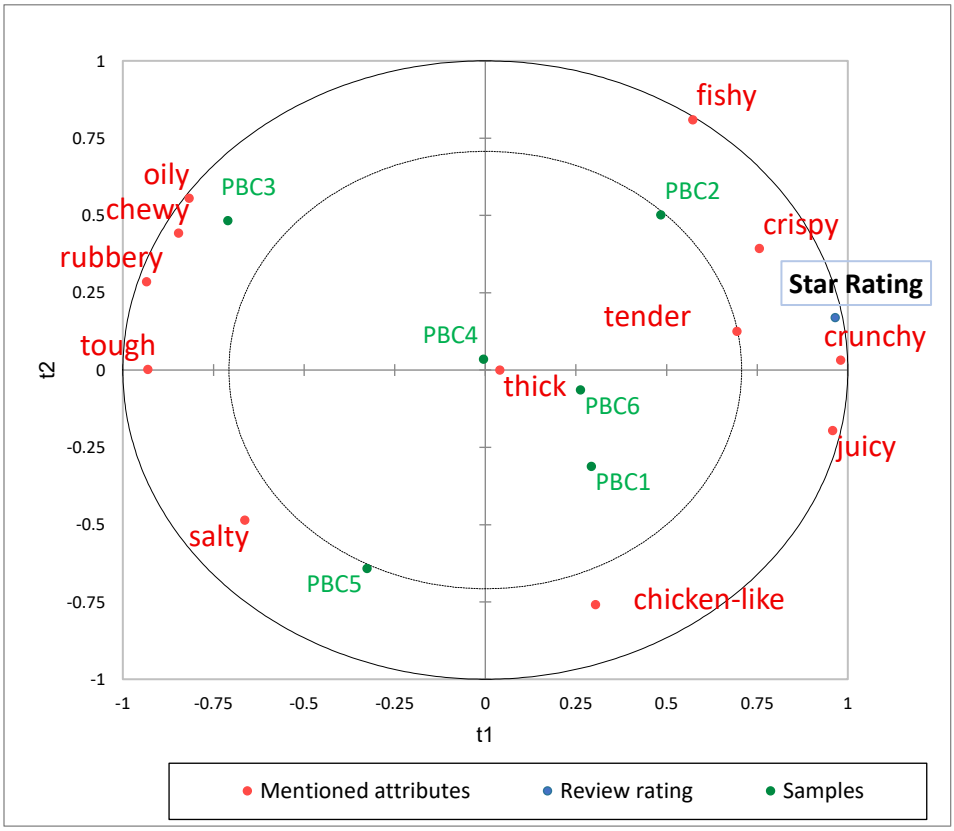
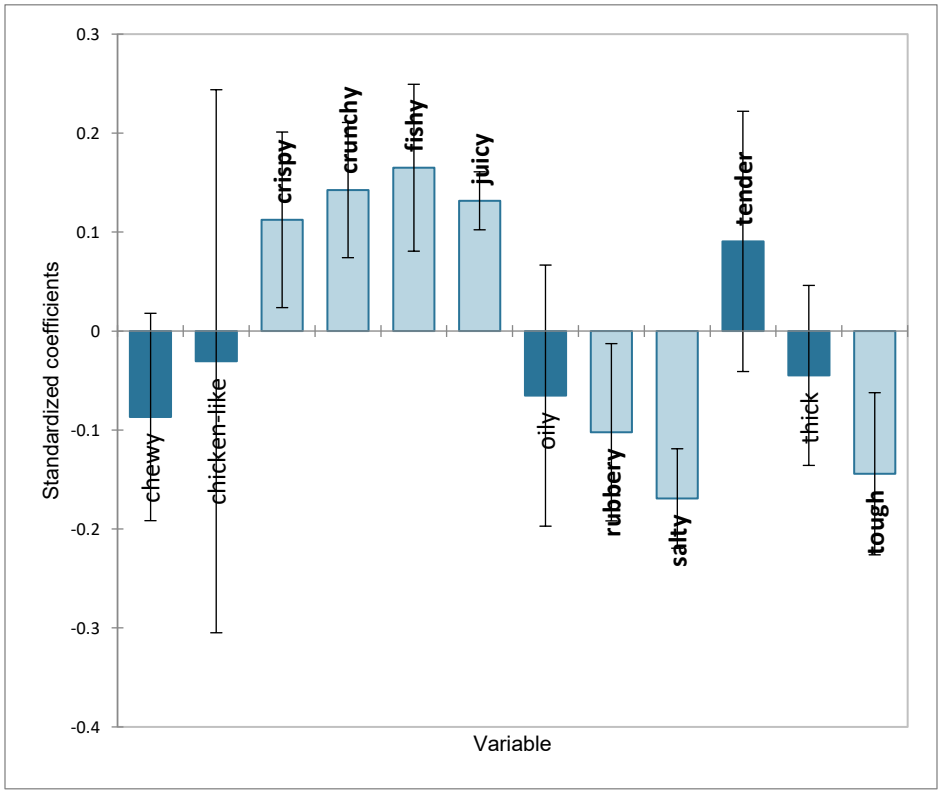


Figure 3.4: Standardized coefficients for sensory drivers of overall liking for the PLSR model



**Attributes in bold with light blue bars indicate significant coefficients based on 95% confidence intervals among those with VIP values greater than 0.8*

Table 3.3: Summary of drivers of liking and disliking identified using the three AI-based approaches

AI Approach	Drivers of Liking	Drivers of Disliking
AI-inferred formulation-based	Fibrous, juicy, savory, brothy, toasted, allium (onion), moist, cohesive	Rubbery, gummy, crumbly, chalky, pasty, dry, beany, green, artificial, flat
Qualitative - review-based without ratings.	Juicy, moist, crispy, crunchy, soft, firm, savory, seasoned, salty	Dry, chewy, rubbery, tough, greasy, oily, bland, spongy
Quantitative - review mentions with PLS-r	Crispy, crunchy, juicy, fishy	Rubbery, salty, tough

Conclusion

This chapter demonstrated the potential of using ChatGPT to analyze e-commerce reviews to identify sensory drivers of liking and disliking of plant-based meat alternatives. By analyzing publicly available Amazon reviews for six plant-based chicken products, the study showed that online reviews can serve as a useful source of unsolicited consumer feedback, particularly for capturing sensory attributes associated with product acceptance in real-world consumption contexts. The ChatGPT-assisted review cleaning process reduced the initial dataset of 631 to 196 sensory-relevant reviews, illustrating that although e-commerce reviews contain valuable sensory information, they also include substantial non-sensory content that must be carefully filtered before analysis. Additionally, consumers tend to have limited sensory vocabulary, hence the absence of an attributes in a review does not definitively equate to a lack of perception but rather that it was not mentioned by the reviewer.

ChatGPT enabled the rapid extraction and organization of sensory descriptors from unstructured text. Across all approaches, including the AI-inferred formulation-based approach, "juicy" and "rubbery" were the only drivers consistently identified across all three approaches as positive and negative drivers, respectively. Overall, the findings suggest that AI-based analysis of online reviews can provide meaningful insights into the sensory characteristics associated with consumer acceptance of plant-based meat alternatives. ChatGPT analysis of the online reviews generated reviewer-based sensory characterizations of the PBMAs and helped to identify differences in sensory terms associated with the products. However, the method also has limitations, including the uncontrolled nature of online reviews, variation in reviewer detail, possible self-selection bias, and the need for human verification of AI-generated sensory classifications. These findings provide a foundation for further work comparing AI-derived

drivers with those from controlled sensory testing, ultimately helping product developers better meet consumer and market demands.

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Chapter 4 - Comparison of Quantitative AI Approach and Consumer CATA Methods

Abstract

Plant-based meat alternatives continue to face sensory challenges that limit broader consumer acceptance, making it critical to identify the attributes that drive their liking and disliking. While controlled consumer sensory tests provide structured and reliable data, online reviews may offer additional insight into real-world consumer experiences. This chapter evaluated whether AI-assisted analysis of online reviews could generate sensory drivers of liking comparable to those obtained from a conventional consumer Check-All-That-Apply (CATA) study. Attributes extracted from AI-analyzed online reviews were compared with consumer CATA data using Multiple Factor Analysis, and Partial Least Squares Regression was used to identify drivers of liking in both datasets. The MFA results showed substantial agreement between the two data sources, with an RV coefficient of 0.781, suggesting that review-derived attributes captured sensory patterns similar to those observed in the controlled consumer test. Both methods emphasized the importance of texture, with "crispy" and "juicy" associated with liking and "tough" associated with disliking. However, the methods differed for some attributes, particularly "fishy," which was associated with higher star ratings in the online reviews and, conversely, with lower liking in the consumer CATA study. These differences highlight the potential effects of uncontrolled review conditions, limited review volume, and possible inconsistencies between attribute mentions and star ratings. Overall, this chapter demonstrates that AI-assisted online review analysis can support preliminary sensory insight generation for plant-based meat alternatives, but its findings should be interpreted alongside controlled consumer sensory data.

Introduction

Consumer sensory methods remain essential for identifying the attributes that influence product liking, particularly for plant-based meat alternatives, where sensory quality is a major barrier to acceptance. Consumer-based sensory characterization approaches such as Check-All-That-Apply (CATA) provide structured consumer responses under controlled testing conditions and allow researchers to relate specific sensory attributes to hedonic ratings using appropriate statistical techniques (Ares et al., 2015). These methods are valuable because they generate targeted data from consumers who evaluate the same products under similar conditions.

At the same time, online reviews offer a different source of consumer insight. Compared with controlled sensory tests, which may not fully represent everyday consumption situations (Jaeger & Porcherot, 2017), e-commerce reviews can reflect real-world product experiences, including how consumers describe products after purchase, preparation, and consumption in everyday settings. Recent studies show that online reviews can contain useful sensory information and may help characterize product differences (Espinosa-Ramos et al., 2025; Yang et al., 2021).

As explored in the third chapter of this research, LLMs such as ChatGPT can analyze online reviews to extract sensory information. However, recent literature on the use of LLMs for sensory analysis consistently emphasizes that these AI-driven approaches are complementary tools rather than replacements for conventional methodologies (Torrico, 2025; Visalli et al., 2025). Furthermore, online reviews have inherent limitations, as critical details about product preparation, consumption context, and consumer demographics are often missing (Espinosa-Ramos et al., 2025). Consequently, comparison with established sensory methods is important to evaluate the agreement and reliability of AI-derived findings.

Multiple factor analysis (MFA) is a multivariate statistical method that helps integrate data from various sources. It reduces data dimensionality, making it possible to detect patterns and similarities among related attributes identified from different sources. MFA also allows the level of agreement between data sources to be evaluated and visualized.

To our knowledge, no study has used a large language model (LLM) to identify drivers of liking for plant-based meat alternatives and then compare those findings with results from a controlled consumer sensory test. By integrating AI-based review analysis with traditional sensory approaches, researchers and product developers may better understand consumer expectations and improve the development of plant-based meat alternatives that better meet sensory and market demands. This study aimed to compare drivers of liking for plant-based meat alternatives identified through consumer research using CATA with those identified through AI analysis of online reviews.

Materials and Methods

Data from the consumer CATA study described in Chapter 2 and the AI-assisted online review analysis described in Chapter 3 were used for the comparison. The consumer CATA study included six plant-based meat alternatives evaluated by 100 consumers, while the online review analysis included 182 sensory-relevant reviews of the same six products. The datasets generated from each approach were used to compare product sensory characterization and drivers of liking across methods.

Multiple factor analysis was performed to compare the attributes extracted from the online reviews to those from the consumer CATA. The analysis was conducted using product-level attribute frequencies, with the six plant-based chicken products represented as rows. Two

groups of variables were included: consumer CATA attributes and online review mentions. The consumer CATA group contained 24 sensory attributes, while the online review mentions group contained 12 sensory attributes. Additionally, A 2x3 table specifying the group labels (consumer CATA and online review mentions) in one column, and the table size in the adjacent column (number of attributes in each group) was created to define the MFA structure and facilitate data analysis in XLSTAT. The resulting data matrix therefore consisted of six products as rows, with 24 CATA attributes and 12 online review attributes as columns. Attribute frequencies for each product were used as the input data. XLSTAT applied the standard MFA procedure to account for differences between the two groups before combining them in the analysis, no manual scaling was performed. The RV coefficient was used to assess the overall similarity between the two datasets. All statistical analyses were performed using XLSTAT (Addinsoft, New York, USA).

Results and Discussion

Comparison of Sensory Characterization in CLT Versus Online Reviews

The sensory characterizations generated from the CLT and online reviews were compared to determine the extent to which both methods described the products similarly. The CLT provided a more controlled and detailed sensory profile, as consumers evaluated all six products using the same predefined CATA terms under standardized conditions. This likely explains why Cochran's Q test identified more attributes as significant in the CLT data (24 out of 32 attributes). In contrast, the online review dataset reflected spontaneous consumer language and real-world product experiences, but the number and context of sensory comments varied across products. As a result, the review data yielded fewer attributes and even fewer significant attributes from Pearson’s chi-square test (6 out of 12 attributes).

Despite these differences, both methods consistently identified some key attributes, including “chicken-like,” “chewy,” “crispy,” and “crunchy,” as important product differentiators. Both approaches also associated PBC3 with negative textural attributes such as “chewy,” “tough,” and “oily” from correspondence analysis, suggesting agreement in the sensory characterization of PBC3 across both controlled and uncontrolled consumer contexts. However, some attributes were captured more clearly in the CLT data, while others appeared only in the online reviews, reflecting how consumers describe products in structured sensory tests with a list of attributes versus natural review settings. These findings suggest that online reviews can provide useful preliminary sensory information, but controlled consumer testing provides more standardized and detailed sensory characterization.

Comparison of AI-Extracted Online Review Dataset to Consumer CATA

To further evaluate the agreement between the two sensory datasets, multiple factor analysis (MFA) was conducted. The first two dimensions explained 78% of the total inertia, as shown in the scree plot (Figure 4.1). The MFA shows substantial agreement between the CLT and online review datasets, with an RV coefficient of 0.781 (Table 4.1). More specifically, the MFA group representation plot (Figure 4.2) illustrates the relative contribution of each data source to the consensus space. Both Consumer CATA and AI-Reviews CATA showed high coordinates (> 0.9) on the F1 axis, indicating similar representation of the two datasets along the primary MFA dimension. However, CATA had a somewhat higher coordinate on the F2 axis than the review dataset, indicating some differences in how the two datasets contributed to the second dimension.

The MFA biplot (Figure 4.3) shows that the first dimension, which accounted for 53.35% of the total inertia, was driven primarily by textural and flavor attributes, with several attributes positioned in opposite directions along F1. For instance, negative textural descriptors were strongly correlated, with "rubbery", "tough", "chewy", and "greasy" forming a tight cluster along the positive F1 axis. These attributes were inversely related to "crispy" and "toasted/brown", which loaded on the negative F1 axis and defined the opposite sensory space. The second dimension accounted for an additional 24.66% of the total inertia, mainly driven by attributes such as "Moist/Juicy", "Meaty/Savory", "Onion", and "Spice/Herb" on the positive F2 axis, contrasting with "Cardboard", "Fishy", and "Particle Residue" on the negative F2 axis. In terms of sample positioning, PBC4 and PBC5 projected into the upper quadrant associated with “moist/juicy,” “meaty/savory,” “onion,” “thick,” and “tender,” while PBC1 and PBC6 aligned closely with “crunchy,” “crispy,” and “chicken-like” on the negative F1 axis. Conversely, PBC3 was located alone on the positive F1 axis and was closely associated with undesirable attributes such as "rubbery", "chewy", "oily", and "tough", whereas PBC2 separated along the lower-left quadrant towards “particle residue,” “tender,” and “crispy”. Additionally, most attributes shared between the two data sources, such as "chicken-like", "chewy", "crispy", "crunchy", and "tough", exhibited similar positioning and directionality in the MFA space, indicating agreement in how these attributes differentiated the products across the two datasets. This agreement is also reflected in the RV coefficient of 0.781.

Figure 4.1: Scree plot for eigenvalues in different dimensions from the multiple factor analysis (MFA)

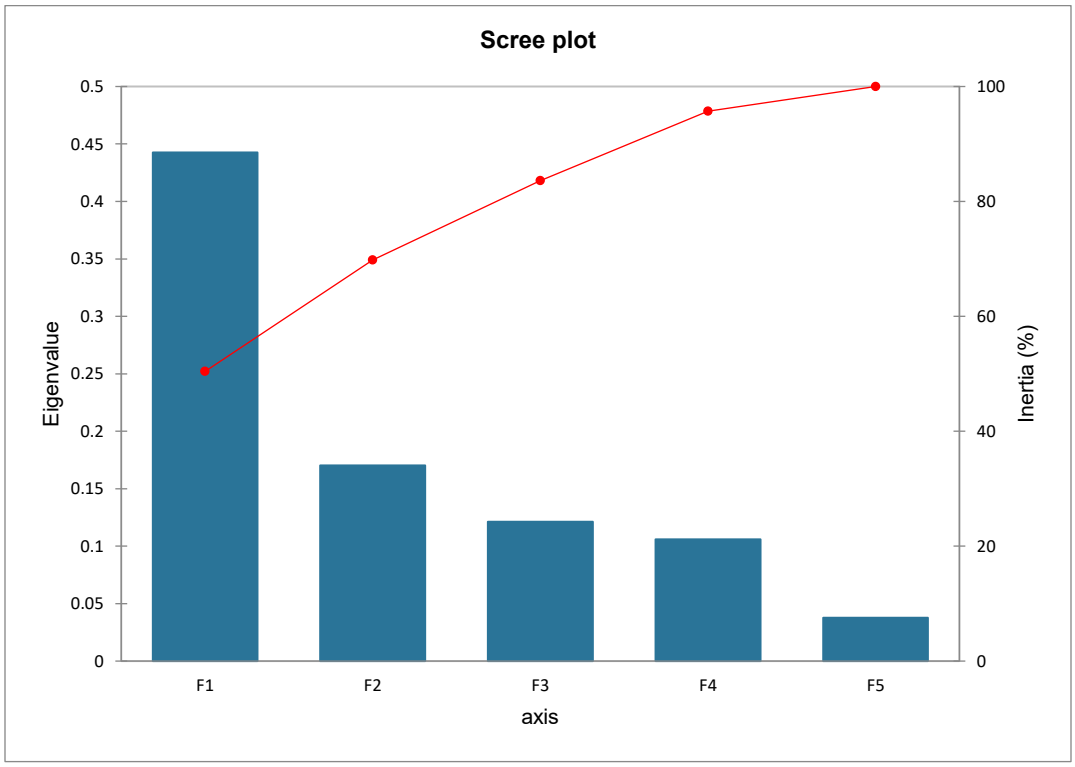


Table 4.1: RV Coefficient from MFA including consumer CATA and online review mentions

	Consumer CATA	Online Review Mentions	MFA
Consumer CATA	1.000	0.781	0.945
Online Review Mentions	0.781	1.000	0.943
MFA	0.945	0.943	1.000

Figure 4.2: MFA group representation of consumer CATA and online review mentions

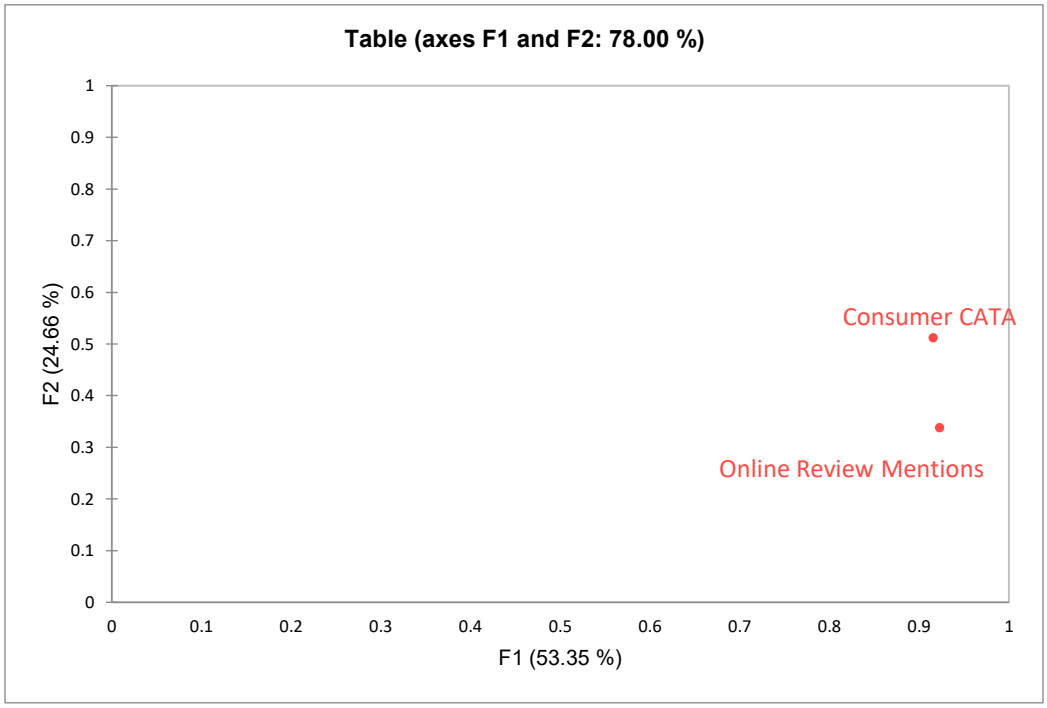
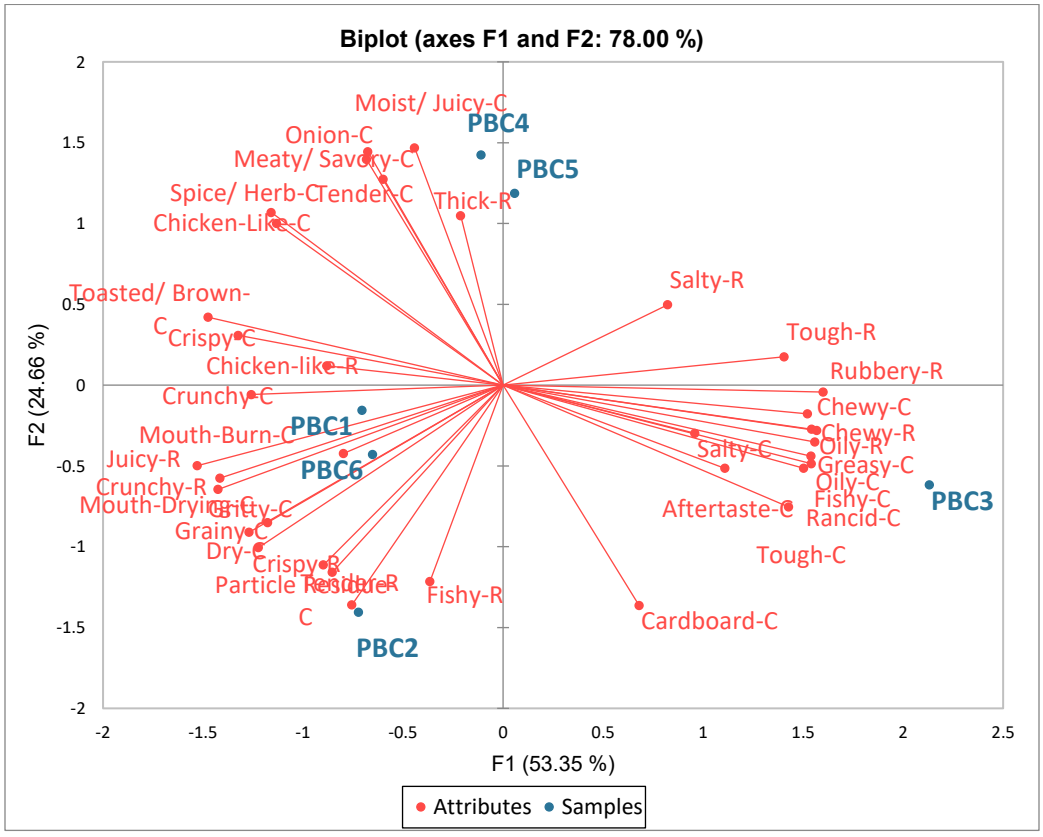


Figure 4.3: MFA biplot of CATA and online review attributes



**Attributes with C attached are CATA attributes, while those with R are review attributes.*

Comparison of Drivers of Liking

Partial least squares regression analysis was used to identify drivers of liking from the CLT and from the online review dataset. The CLT identified 11 significant drivers, including “chicken-like,” “meaty/savory,” “tender,” “spice/herb,” “moist/juicy,” “toasted/brown,” “onion,” “crispy,” “cardboard,” “tough,” and “fishy,” while the online review dataset identified seven significant drivers: “crispy,” “crunchy,” “juicy,” “fishy,” “tough,” “salty,” and “rubbery.” Although the two methods did not entirely identify identical drivers, both consistently highlighted texture-related attributes, particularly “juicy” and “crispy,” as significant predictors of liking, while “tough” drove disliking. These results underscore the importance of textural attributes in consumer acceptance of PBMAs. Differences between the two methods may be attributable to low review volume, which can lead to inadequate data points for AI analysis and subsequent statistical analyses; the 12 most frequently mentioned attributes cumulatively ranged from 6 to 38 mentions across all six products. Additionally, online reviews are uncontrolled, and ratings can be influenced by factors beyond sensory quality, such as price, convenience, product expectations, preparation method, or overall purchase experience, even when not explicitly stated in the review. This limitation was illustrated by the attribute “fishy.” While it was a significant driver of disliking in the CLT, consistent with expectations for plant-based meat alternatives, it appeared as a significant positive predictor of star ratings in the online review dataset. This may reflect the difficulty of linking attribute mentions directly to star ratings without knowing the reviewer’s intended meaning or context. It may also reflect term ambiguity inherent in consumer-generated data, as the same sensory term may be used by consumers to describe different perceptions or experiences. The different positioning of “fishy” between the CATA and review data in the MFA further suggests that the term may not have represented the same

sensory meaning in the two datasets. Overall, these findings indicate that AI-assisted analysis of online reviews can provide useful preliminary insights into broad sensory drivers of liking, but conventional consumer testing remains necessary to compare with and help interpret these findings more accurately.

Conclusion

This chapter compared drivers of liking for plant-based chicken products using consumer CATA data and AI-assisted analysis of online reviews. Both approaches identified textural attributes, including “crispy” and “juicy”, as significant drivers of liking, while “tough” consistently drove disliking. The MFA results also showed substantial agreement between the consumer CATA and review-derived data with an RV coefficient of 0.781, suggesting that AI-assisted review analysis can capture sensory patterns similar to those obtained from controlled consumer testing.

However, the two methods differed in some cases, particularly for attributes such as fishy, which showed opposite relationships with liking and star ratings across the two datasets. This highlights the limitations of online reviews, including variation in review detail, inadequate consumer context, term ambiguity, and possible inconsistencies between attribute mentions and star ratings. More work is needed to further evaluate the agreement between AI-based methods and controlled consumer sensory methods. Future research should also focus on product categories with larger volumes of online reviews. Nonetheless, this study positions AI-assisted online review analysis as a rapid and useful complementary tool for generating preliminary sensory insights, rather than a replacement for conventional sensory and consumer testing.

Applications

This study highlights the potential of AI-assisted online review analysis as a rapid complementary tool for identifying sensory drivers of liking in plant-based meat alternatives. By extracting sensory information from publicly available consumer-generated reviews, food researchers and product developers can gain early insight into attributes that are associated with consumer acceptance, such as crispiness, juiciness, and toughness. These findings can support preliminary product screening and help manufacturers prioritize texture-related improvements in plant-based chicken products before conducting more costly and time-intensive sensory and consumer studies.

The research also provides a practical framework for integrating online review analysis with conventional sensory methods. Although AI-assisted review analysis identified sensory patterns similar to those from consumer CATA data, the findings also show the importance of comparing review-derived findings with those obtained through controlled consumer testing. Food companies can use this combined approach to guide product reformulation, benchmark competing products, and identify key sensory attributes associated with consumer liking. This would facilitate faster, more cost-effective product development while still maintaining the reliability of traditional sensory and consumer research methods.

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Appendix A - Screener and Questionnaire Used in Consumer Study

Screener

Q1. What is your gender?

Male

Female

Q2. Are you currently pregnant or nursing?

Yes

No

Q3. Which of the following categories best describes your current age?

17 or under

18 - 25

26 - 35

36 - 45

46 - 55

56 - 65

66 - 75

76 or older

Q4. Do you, or does any member of your immediate family, work for any of the following types of companies? (check all that apply)

Advertising or public relations

Market research

Broadcast or print media

Food or beverage manufacturing company

Grocery store, supermarket, or convenience store

Q5. Auto manufacturing/sales

Credit card company

Bank or other financial institution

None of the above

Q6. Have you participated in any type of market research study either at K-State or another testing facility in the past 3 months

Yes

No

Q7. Are you currently scheduled to participate in any market research studies either at K-State or another testing facility?

Yes

No

Q8. Are you allergic or sensitive to any of the following foods? (check all that apply)

Wheat (gluten)

Soybean

Egg

Milk

Fish

Crustacean shellfish

Tree Nut

Sesame

Peanut

Other:

I am NOT allergic to any of the above

Q9. When it comes to grocery shopping and deciding what brands to buy, would you say…?

I do all or most of the grocery shopping for my household

I share the responsibility equally with someone else

Someone else in my household does most of the shopping

Someone else in my household does all the shopping

Q10. Which of the following foods have you consumed in the past month (check all that apply)

Milk

Plant-Based Milk

Fish/Seafood

Beef

Chicken

Plant-Based Meat

Fresh Vegetables

Frozen Vegetables

None of the above

Q11. How interested or uninterested are you in plant-based meat alternatives?

Not At All Interested

Slightly interested

Somewhat interested

Very interested

Extremely interested

Q12. Which of the following types of plant-based meat products would you be willing to try? (check all that apply)

Plant-Based Bacon

Plant-Based Chicken

Plant-Based Sausage

Plant-Based Beef

Other (please specify)

None of the above

"YOU are being considered for a Plant-Based Chicken study.

Study Requirements: Do NOT wear any type of fragrance, body lotion or spray, or any other strong-smelling products on the day of the study. You will receive a reminder email 24 hours before the study. Please have your ID out and visible to the receptionist when you enter the

building. You may be required to eat an unsalted saltine cracker during the study. Please use the restroom before arriving at the center to minimize access to public spaces. If you need reading glasses, please bring them to the session. This study is confidential; please don't discuss any of the details with anyone. DO NOT eat or drink anything but water for 30 minutes prior to your session, including chewing gum. If you have experienced COVID-19 symptoms, a fever, or any flu-like symptoms in the past 72 hours, please cancel your session and do not attend the study. Please refrain from smoking or vaping while on K-State Olathe property. No children are allowed at the study; please schedule daycare.

Do you agree to adhere to the requirements above? (Note: You could be disqualified during check-in if you have not met these requirements.)

Yes

No

You are being CONSIDERED for a Graduate Student's Plant-Based Chicken study on Monday, December 15th at the Olathe campus. The study will take approximately 35 minutes, and you will be compensated $30 for your time. Are you willing to participate?

Yes

No, I'm not willing to participate

Questionnaire

"Please wait for your FIRST sample.

While waiting for your sample, please take a sip of water and bite of cracker to clean your mouth.

When you have received sample ${SAMPLEBC}click next to continue.

DO NOT TASTE YOUR SAMPLE UNTIL INSTRUCTED."

Q1. How much do you like or dislike the overall appearance of this plant-based chicken piece?

Dislike extremely – Like Extremely (9-point)

Q2. How much do you like or dislike the aroma of this plant-based chicken piece?

Dislike extremely – Like Extremely (9-point)

Q3. Considering the appearance, aroma, taste, and texture, of this plant-based chicken piece, how much do you like or dislike it overall

Dislike extremely – Like Extremely (9-point)

Q4. How well does this sample meet your expectation for a plant-based chicken piece?

Much Worse Than Expected

Worse Than Expected

Meets Expectations

Better than Expected

Much Better Than Expected

Q5. Write a review about the sensory properties of this plant-based chicken piece as if you were submitting it to an e-commerce platform where you purchased the product

Q6. How much do you like or dislike the flavor of plant-based chicken piece?

Dislike extremely – Like Extremely (9-point)

Q7. How much do you like or dislike the texture of plant-based chicken piece?

Dislike extremely – Like Extremely (9-point)

Q8. How much do you like or dislike the aftertaste of plant-based chicken piece?

Dislike extremely – Like Extremely (9-point)

"Take another bite of sample ${SAMPLEBC}, about half of your remaining piece.

Q9. Thinking about its flavor and mouthfeel only, check at least five of the attributes listed below that apply.

Salty

Meaty/ Savory

Chicken-Like

Beany

Sweet

Soy

Sour

Oily

Grainy

Onion

Spice/ Herb

Cardboard

Fishy

Mouth-Burn

Green/ Vegetable

Toasted/ Brown

Rancid

Aftertaste

Mouth-Drying

Bitter

Particle Residue

Other (please specify)

"Take another bite of sample ${SAMPLEBC} (the remaining piece) before proceeding!

Q10. Thinking about its texture only, check at least two of the attributes listed below that apply."

Chewy

Crispy

Tender

Dry

Firm

Crunchy

Moist/ Juicy

Greasy

Gritty

Tough

Toothpacking

Other (please specify)

Q11. When thinking of plant-based chicken pieces, which of the following flavor and mouthfeel attributes would make an ideal piece for you? Please select a minimum of five (5) attributes.

Salty

Meaty/ Savory

Chicken-Like

Beany

Sweet

Soy

Sour

Oily

Grainy

Onion

Spice/ Herb

Cardboard

Fishy

Mouth-Burn

Green/ Vegetable

Toasted/ Brown

Rancid

Aftertaste

Mouth-Drying

Bitter

Particle Residue

Other (please specify)

Q12. When thinking of plant-based chicken pieces, which of the following texture attributes would make an ideal piece for you? Please select a minimum of two (2) attributes.

Chewy

Crispy

Tender

Dry

Firm

Crunchy

Moist/ Juicy

Greasy

Gritty

Tough

Toothpacking

Other (please specify)

Q13. How often do you typically consume plant-based meat, either as an ingredient in a meal or as the main entree, at home or in a restaurant?

More than once a week

Once a week

2 to 3 times a month

Once a month

1 to 2 times a year

Less than once a year

Never

Q14. Which of the following benefits of plant-based meat would encourage you to purchase and try a new plant-based meat product? (Check all that apply)

Sustainability

Packaging

Cost/ Affordability

Health Benefits

Convenience

Animal Welfare

Variety of flavor and meal options

Other (please specify)

None of the above

Q15. What concerns, if any, do you have about plant-based meat products? (Check all that apply)

Cost

Health

Highly Processed

Long Ingredient List

Complicated to Cook

Taste

Texture

Other (please specify)

None of the above

Q16. What is your gender?

Male

Female

Q17. Which of the following categories best describes your current age?

18-25

26-35

36-45

46-55

56-65

66-75

Q18. What is your dietary preference?

Vegan

Flexitarian

Vegetarian

Pescatarian

Omnivore

Carnivore

I do not know