FlavorCharter: Development of a Smartphone App for Quantifying Food Flavor

Francesco Botto
Department of Computer Science
University of Illinois Chicago
Chicago, IL
fbott1@uic.edu

Guadalupe Canahuate
Department of Electrical and Computer Engineering
University of Iowa
Iowa City, IA
guadalupe-canahuate@uiowa.edu

Xinhua Zhang
Department of Computer Science
University of Illinois Chicago
Chicago, IL
zhangx@uic.edu

C. David Fuller
Department of Radiation Oncology
University of Texas MD Anderson Cancer Center
Houston, TX
cdfuller@mdanderson.org

G. Elisabeta Marai
Department of Computer Science
University of Illinois Chicago
Chicago, IL
gmarai@uic.edu

***Abstract*—We present the design and development of a crowd-sourced, data-driven approach to quantifying the flavor of specific foods. Our approach leverages an interactive smartphone app with a client-server architecture, and supports future stratified analysis based on dietary and demographic factors. This approach has the potential to document taste loss and to empower patients to describe taste loss symptoms in a more precise, standardized language.**

***Index Terms*—flavor, taste loss, head and neck cancer**

I. Introduction

Food enjoyment is an important component of quality of life, and most humans take the ability to detect food flavor for granted. However, not everyone is that fortunate. Taste loss (dysgeusia or altered taste) is a common long-term side effect in head and neck cancer (HNC) patients, affecting a large percentage of patients during and after treatment, in particular during and after radiotherapy. Dysgeusia is experienced by 51–100% of patients at the end of radiotherapy and 23–50% at 1–2 years after treatment [15]. This taste dysfunction can result from radiation-related damage to the soft tissues in the head and neck [37], [40]–[42], including taste buds and nerves, and is a significant toxicity that negatively impacts quality of life [12], [13], [39]. In dysgeusia, patients may experience a dulled, changed, or completely lost sense of taste and enjoyment in food [34]. This can lead to decreased appetite and reduced food intake, impacting overall nutrition and quality of life [2], [7], [26]. The resultant poor nutritional choices can then contribute to sarcopenia, or muscle wasting [22], [29], which is directly associated with increased mortality and poorer clinical outcomes across multiple datasets [3], [6], [14]. Loss of taste can also be a symptom of infections like COVID-19, the common cold, or sinus infections, as well as neurological conditions like Alzheimer's, Parkinson's, or multiple sclerosis. Other causes include aging (people over 50 experience a reduction in the number of taste buds), certain medications, poor oral hygiene, vitamin deficiencies (especially zinc and B12), acid reflux, and head or nerve injury. However, dysgeusia has been studied mostly in the context of head and neck cancer [31], [38], due to its prevalence in this condition.

Strategies to improve taste function and nutrition include working with a healthcare team, such as nutritionists, to manage taste and dietary issues [4], [9]. However, these strategies are severely impaired by a lack of data and understanding regarding flavor perception in normal individuals, and the lack of precise descriptions of taste loss in head and neck patients. For example, patients in the clinic may state [actual quotes]: *"Things taste different"* without being able to explain how when prompted by the clinician; or *"Doesn't taste good"*, *"It tastes bland"*, *"I can handle sweet, but chocolate cake is terrible"*, or *"Tastes like asphalt / cardboard / mud / dirt"*.

To overcome these critical issues, we present the development of a crowd-sourced, data-driven smartphone approach to quantifying the subjective perception of flavor in a set of foods. Following a computational approach to flavor quantification facilitates access to data from a broad population, and provides good potential representation of variability with factors like age or regional cuisine. It also has the potential to empower patients to describe taste loss symptoms in a precise, standardized language, and to improve patient-doctor communication through shared verbiage.

II. Background and Related Work

The biomedical clinical perspective on taste and flavor is generally aligned with the chemical perception through the taste buds (sweet, salty, sour, bitter, and umami). Biomedical research on taste loss is focused on the key molecular mechanisms underlying the phenomenon, including genetics, cellular regeneration, and the role of inflammation, age, metabolism and obesity on taste perception. Flavor is however multidimensional, and involves interactions of taste and smell [10], [23]. Recent insights from the COVID-19 pandemic have further

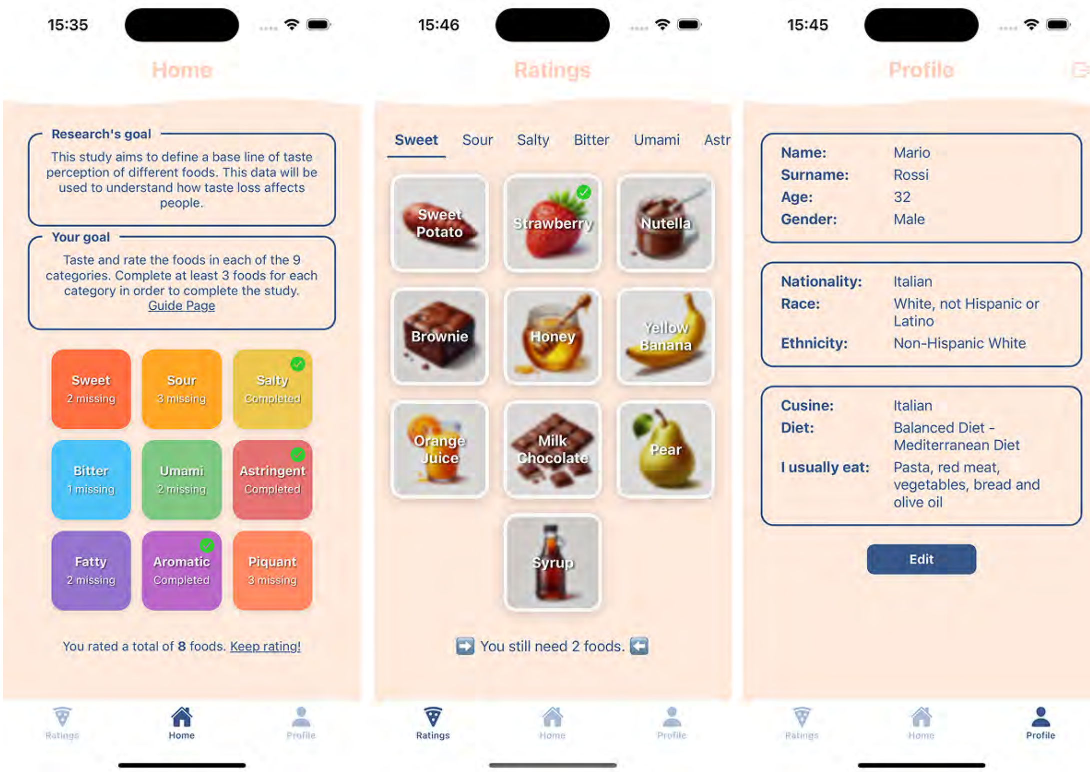

Fig. 1. Application front-end, showing the Home, Ratings, and Profile screens.

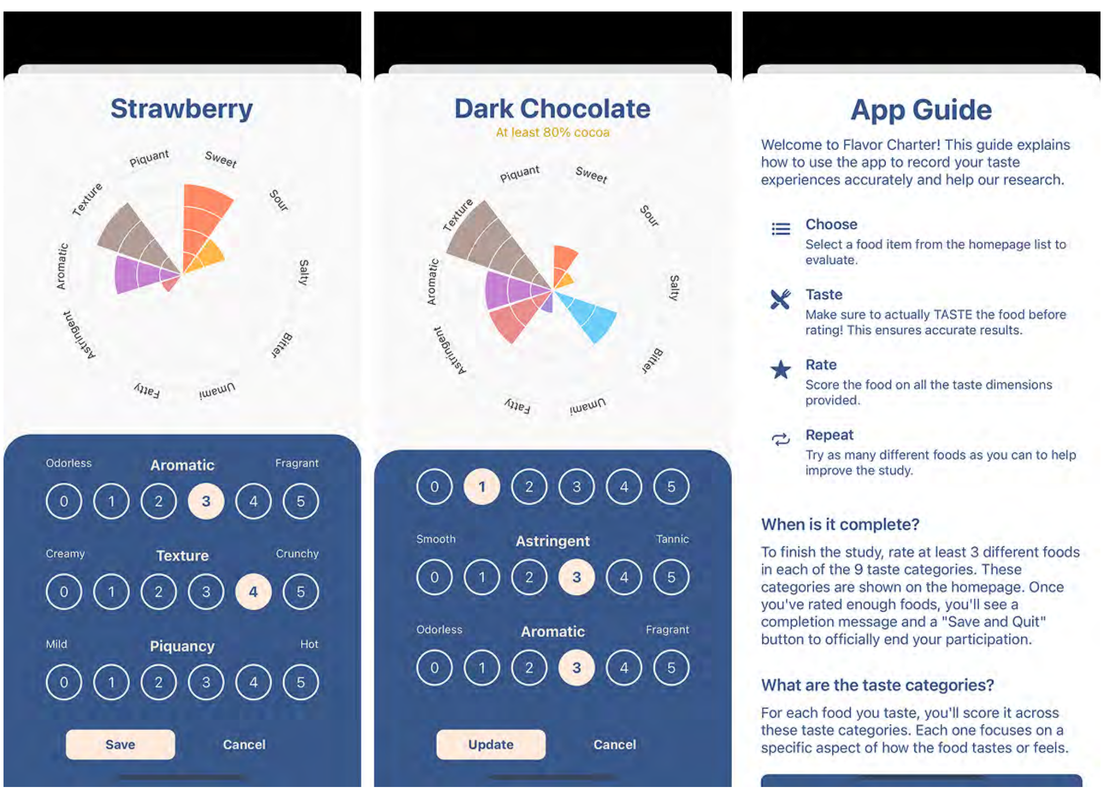

Fig. 2. Application front-end, showing the rating screens and the application guide.

connected the sense of smell and taste, and have shown that olfactory training can improve the senses of smell and taste after viral infections by leveraging neuroplasticity.

Patient reported outcomes collected through questionnaires typically quantify the degree of taste loss, but do not detail any specific dimensions of taste loss. The MD Anderson Symptom Inventory (MDASI) [5] addresses taste loss through its Head and Neck Module (MDASI-HN), which includes a specific item on "problems with tasting". The MDASI-HN measures the severity of a patient's tasting problems based on their self-reported experience in the last 24 hours. It is a patient-reported outcome (PRO) measure, meaning it captures the subjective experience of the patient. The questionnaire is typically administered weekly during treatment to track the progression of symptoms. Like all MDASI symptom items, the tasting problem is rated on a 0–10 scale, where 0 is "not present" and 10 is "as bad as you can imagine". In clinical practice, the MDASI-HN is sometimes used alongside other tests to provide a comprehensive assessment of taste. For example, some studies use objective "taste strips", liquid taste stimuli presented in drops, or edible films that incorporate chemosensory stimuli [11] in combination with the MDASI-HN to test for specific taste qualities (sweet, sour, salty, and bitter) and concentrations. This approach combines the patient's subjective perception of taste loss with an objective, measured result.

Other works consider Likert scales of 4 dimensions of gustatory disturbances: intensity of taste, discomfort, phantogeusie and parageusia, and general alterations of taste [32], which are not precise enough to be actionable. Another approach has developed The Taste Liking Questionnaire (TasteLQ), a validated tool developed for the Danish population to measure liking for various tastes and oral sensations, including basic tastes (sweet, sour, salty, bitter, umami), fat sensation, pungency, and astringency, through 44 food items [17]. There are no existing distributed, data-driven approaches that leverage mobile technology to quantify food flavor.

III. Methods

A. Design Process

The requirements for our approach build on several interviews with HNC radiation oncology clinicians at a major international cancer treatment center, as part of a long term inter-disciplinary collaboration that spans more than a decade. These interviews revealed how imprecise descriptions of taste loss during clinic appointments led to frustration and a sense of powerlessness on both the HNC patient and provider side. They also revealed that the five classical measures of taste, aligned with the taste bud types, were inadequate in the clinic (e.g., patients described a loss of piquancy, or unpleasant textures). Together with the clinicians, we then performed a literature survey to better understand the multiple dimensions of taste and flavor. We then designed a protocol for collecting data through a smart phone app. The protocol was further enhanced through feedback from our Institutional Review Board, in particular with respect to using layman verbiage when describing taste or flavor (e.g., *savory* rather than *umami*). We designed and developed a smart phone app (Fig. 1 and Fig. 2) based on this protocol. We used an Activity-Centered Design process [21], through which we iteratively incorporated feedback from collaborators and early testers to refine the final design.

B. Flavor and Taste Dimensions

Following a review of taste and flavor dimensions as discussed in the culinary literature [8], [25], biomedical literature [17], [28], a social media guide to flavor profiles [27], and multiple discussions with the HNC clinicians, we agreed on the following relevant dimensions for studying taste loss:

- Sweet
- Salty
- Sour
- Bitter
- Savory
- Fatty
- Astringent
- Aromatic
- Texture
- Piquancy

The first five dimensions (*Sweet, Salty, Sour, Bitter,* and *Savory*/umami) are associated with the taste bud types, where *Savory*/umami denotes the meaty "mouth-filling" taste noticeable in foods like anchovies, blue cheese, or mushrooms. *Fatty* is the unique sensation of dietary fat detected by the tongue, distinct from texture and aroma, and which is sometimes considered the sixth basic taste. *Astringent* denotes a sensory sensation of dryness, roughness, and puckering in the mouth, caused by compounds called tannins and polyphenols that bind to salivary proteins, and detectable in red wine, unripe fruit, walnuts, or tea. *Aromatic* denotes what is perceived by the nose, and it is thought to be responsible for as much as 80% or more of flavor; aromatic ingredients include fresh herbs, spices, or grated lemon zest. *Texture* denotes the feel, appearance, or consistency of food, and can range from creamy to crunchy and crispy. *Piquancy* denotes the incorrect mouthfeel of “hotness”, meaning piquancy's “sharpness” and/or “spiciness”.

From other dimensions present in our survey, we excluded *Temperature* [8] and *Heat* [25], which are related to the process of cooking or baking the food, were not directly related to taste loss, and were also too difficult to control for. We also did not include *The X Factor* [8], which denotes what is perceived through our five physical senses including sight, and also emotionally, mentally, and even spiritually. However, we did include diet and cuisine among the demographics data collected. In addition, we included a comment free-text box for flavor or taste perceptions not covered by these dimensions (e.g., metallic, asphalt, cardboard etc.).

C. Demographics Data

Through discussions with our clinician collaborators we compiled the following list of demographics data to collect:

Sweet	Salty	Sour	Bitter	Umami	Fatty	Astringent	Piquant	Aromatic
Sweet Potato	Soy Sauce	Yogurt	Dark Coffee	Soy Sauce	Olive Oil	Red Wine	Black Pepper	Strawberry
Strawberry	French Fries	White Vinegar	Dark Chocolate	Parmesan	Avocado	Black Tea	Chili	Garlic
Nutella	Potato Chips	Pickles	Tonic Water	Salami	Milk	Walnuts	Ginger	Parmesan
Brownie	Parmesan	Lemon Slice		Garlic	Almonds	Dark Coffee	Yellow Onion	Dark Coffee
Honey		Orange Juice		Bacon	Eggs			Dark Chocolate
Yellow Banana					Dark Chocolate			Black Tea
Orange Juice					Parmesan			Yellow Onion
Milk Chocolate					Bacon			
Pear								
Syrup								

TABLE I
FOODS GROUPED BY DOMINANT TASTE DIMENSION

- Age Group
- Gender
- Nationality
- Ethnicity/Race
- Regional Cuisine (Indian, Mexican, Chinese, Thai, other)
- Diet (e.g., low-carb/vegan/gluten-free)
- What foods do you normally eat

The Age Group information was included due to the documented relationship between taste loss and advanced age [30]. The Regional Cuisine list was tailored in this case to capture spicy cuisine and to reflect the population typically treated at the medical center. The Diet information was included due to evidence that habitual carbohydrate consumption affects a person's sensitivity to sweetness, with lower sugar diets potentially increasing sensitivity to sweet tastes [16].

D. Food List Design

The current food list was carefully curated following a structured selection process. We began by collecting commonly consumed food items from online sources and dietary surveys in the United States. The preliminary list was then compared with the validated item pool of the Danish Taste Liking Questionnaire (TasteQL), which provided a scientifically grounded reference for taste-based categorization [17]. To finalize the list, we applied four key principles:

- Familiarity: foods should be widely recognized, especially by U.S. participants
- Clear Taste Profile: each food should strongly represent one primary taste dimension
- Ease Of Use: items must be ready-to-eat without requiring cooking or preparation
- Balanced Representation: ensuring that each taste group is covered by at least three examples to avoid bias

We also excluded items with high taste variability (taste heavily dependent on brand or preparation) or with multiple overlapping dominant flavors. Items with variability due to varying ripeness, added ingredients or flavorings were reduced to the simplest version and explicitly labeled (e.g., "yogurt: plain, unsweetened", "banana: yellow, ripe"). Foods requiring preparation were either removed or explicitly labeled with usage instructions. The resulting set (Table I) consists of 36 items that are consistent, easy to evaluate, and taste-specific, making them particularly well suited for the goals of this study.

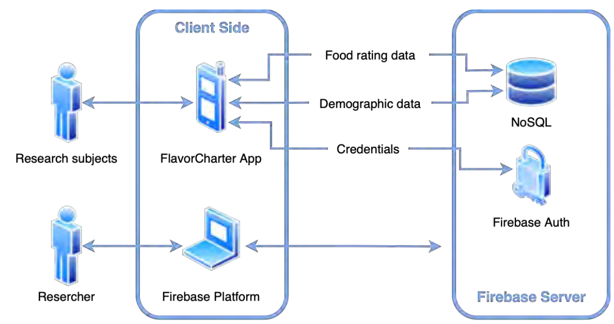

Fig. 3. System architecture for the mobile application, showing the client and server sides of the application.

E. System Architecture

The mobile application (Fig. 3) is developed using the Expo Framework (React Native), providing a cross-platform solution for both Android and iOS. The backend relies entirely on Firebase, a cloud-based Backend-as-a-Service (BaaS) platform, where Firestore is used as the real-time NoSQL database to store user data, and Firebase Authentication manages secure user login and session handling. The Firestore database is structured to separate static user information from dynamic input. Each user has a unique document containing two key sections: a single document for demographic data and a subcollection for individual food taste ratings. This design supports modular data access and efficient querying, while keeping a clear separation of concerns.

IV. RESULTS AND DISCUSSION

Figure 1 shows the resulting application front-end. Figure 2 shows the food rating interface for two types of food, and the application help screen. The front-end leverages a Kiviat diagram (a filled-in radar chart) to encode the multivariate flavor dimensions, due to its proven effectiveness in multivariate data similarity visual detection [20].

In a controlled experiment, we provided twelve subjects with food samples and asked them to rate their flavor profile. Some subjects elected to not try some of the foods. Figure 4 shows the mean and example flavor profile ratings for Dark Chocolate. Bitterness is prevalent. The quantitative flavor profile is shown in Table II. Figure 5 shows the mean and example profile ratings for Almond. All responders identified

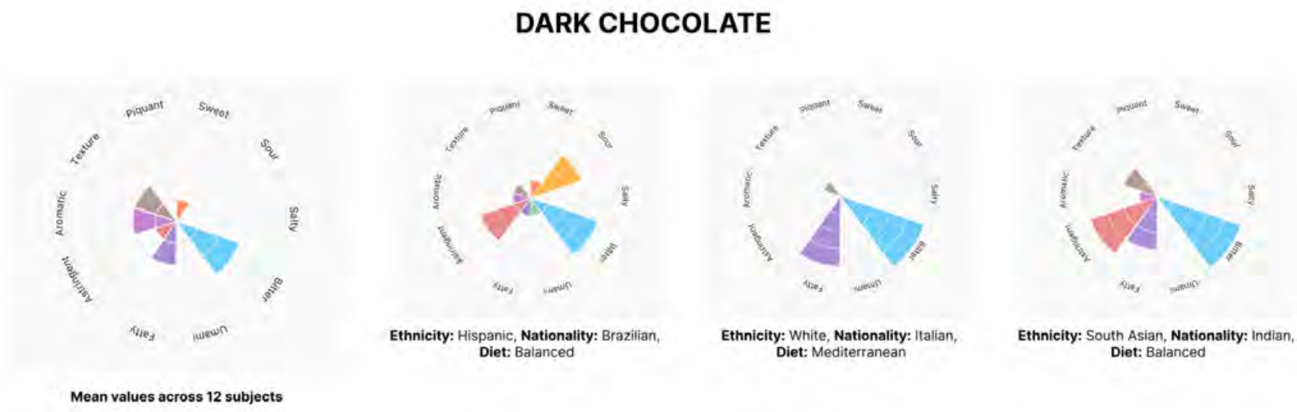

Fig. 4. Dark chocolate flavor profile mean ratings (twelve responders), and three individual ratings from different responders, along with the ethnicity, nationality, and diet of each responder.

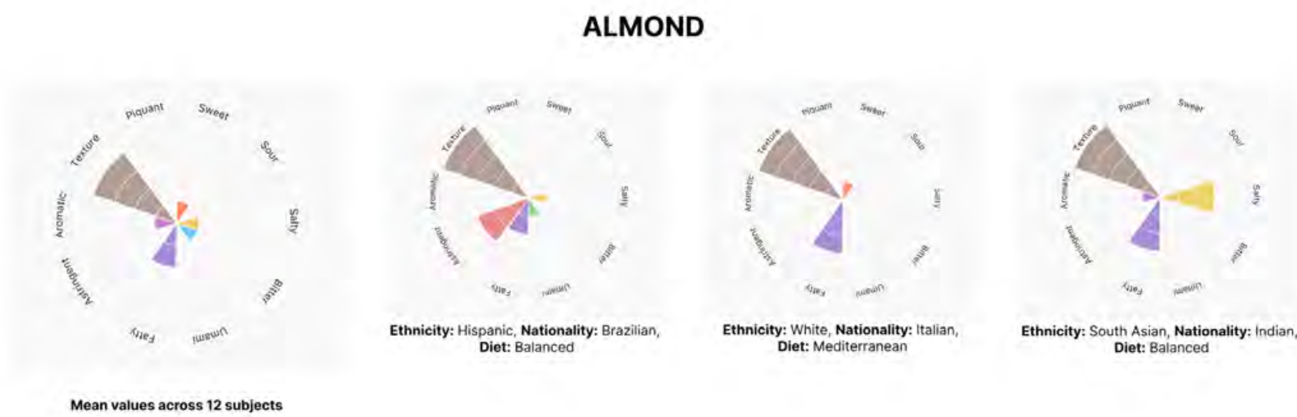

Fig. 5. Almond flavor profile mean ratings (twelve responders), and three individual ratings from different responders, along with the ethnicity, nationality, and diet of each responder.

the crunchy texture. Some responders, but not all, detected also bitterness. One responder identified also sweetness. The quantitative flavor profile is shown in Table III. Figure 6 shows the mean flavor profile for Strawberry across twelve respondents, and example flavor profile ratings from three of these individuals. While all responders identify the food as sweet and sour with an olfactory note (aroma), one responder also identified an umami (savory) component, and several responders identified a note of bitterness. The quantitative flavor profile is shown in Table IV. Despite individual variations in demographics and diet, the flavor profiles appear to be remarkably consistent across testers. The individual variations among subjects are also fascinating.

TABLE II
QUANTIFIED FLAVOR PROFILE FOR DARK CHOCOLATE (12 RESPONDERS)

Dimension	Mean $\pm$ Stdev
Sweet	1.42 ± 1.00
Sour	0.50 ± 1.17
Salty	0.33 ± 0.65
Bitter	3.50 ± 1.09
Umami	0.08 ± 0.29
Fatty	1.58 ± 1.16
Astringent	1.00 ± 1.65
Aromatic	1.67 ± 0.98
Texture	2.17 ± 1.40
Piquant	0.00 ± 0.00

In an additional small scale feasibility pilot test, a different set of three testers used the app at home for a short period of time (2-3 days). The responders (R1, R2, R3) rated food items they already had in their homes. Due to the limited duration, each responder provided good coverage of the food

TABLE III
QUANTIFIED FLAVOR PROFILE FOR ALMONDS (12 RESPONDERS)

Dimension	**Mean ± Stdev**
Sweet	0.75 ± 1.22
Sour	0.00 ± 0.00
Salty	0.83 ± 1.11
Bitter	0.83 ± 1.59
Umami	0.17 ± 0.39
Fatty	2.17 ± 1.47
Astringent	0.42 ± 0.90
Aromatic	0.50 ± 0.67
Texture	4.25 ± 1.48
Piquant	0.00 ± 0.00

TABLE IV
QUANTIFIED FLAVOR PROFILE FOR STRAWBERRY (12 RESPONDERS)

Dimension	**Mean ± Stdev**
Sweet	3.00 ± 0.82
Sour	2.38 ± 1.19
Salty	0.23 ± 0.44
Bitter	0.38 ± 1.12
Umami	0.08 ± 0.28
Fatty	0.00 ± 0.00
Astringent	0.69 ± 0.75
Aromatic	2.23 ± 1.42
Texture	1.85 ± 1.28
Piquant	0.00 ± 0.00

categories in terms of taste dimensions (9-20 foods profiled, spanning in the case of each responder all of the 9 categories), but they did not rate a large number of foods per category. As a result, the three responders had a relatively small number of foods in common: Yogurt, Strawberry, Dark Chocolate, and Tonic Water. Figure 7 shows the flavor profile ratings from these respondents for Strawberry. All responders identified the food as sweet. R1 did not detect an olfactory note (aroma), and identified an umami (savory) component. Despite these variations, which may or not be due to variability in the food (e.g., R3 noted their variation was an Oishii strawberry, a varietal advertising "exceptional sweetness, a delicate aroma, a firmer texture, and a superior flavor") the overall profile is similar across the three responders. Figure 8 shows the flavor profile ratings from these respondents for Tonic Water. All three responders identified a bitter component. R1 did not identify an astringent note at all, and again indicated an umami/savory note.

These results support the feasibility of this approach. Even if patients would rate a relatively small number of foods at home, the information would be enough, when compared against the normal population and tracked over time, to pin point the specific dimensions of flavor being affected, their trajectory over time, and their response to targeted interventions. Beyond feasibility, these preliminary results illustrate the importance of collecting large scale data from all types of people, in particular as age >50 dulls the sense of taste, and most HNC patients are older than 65.

The design of our solution generalizes well to other sets of custom foods, demographics, or flavor characteristics. The radar chart encoding is effective for up to a few dozen features. Our overall solution scales well with a large number of application clients.

V. CONCLUSION AND FUTURE WORK

In this work we presented the design and development of a crowd-sourced, data-driven approach to quantifying the flavor of specific foods. Our solution proposes an interactive smart phone app backed up by a client-server architecture, which could be leveraged for telehealth [19], [24] across populations [18], [33]. This solution was developed through participatory design with HNC clinicians, and is informed by the biomedical literature and the culinary literature. The resulting app will allow us to generate a rich dataset of flavor perceptions, annotated with dietary and demographic factors. The resulting dataset may help clarify other important questions related to diet, flavor, and culinary enjoyment.

Beyond establishing a flavor baseline across a wide variety of individuals, this approach has the potential to empower head and neck cancer patients to describe taste loss symptoms in a more precise, standardized language. In future work, we plan to track changes over time in an individual's ratings of food flavor, to quantify and compare the data provided by head and neck cancer patients against the baseline measurements while accounting for missing data [1], [35], [36], [43], and to develop computational nutritional and dietary interventions to improve the quality of life of patients during and after radiation treatment.

ACKNOWLEDGMENT

The authors' work is supported by the U.S. National Institutes of Health through awards NIH NCI R01CA258827 and NIH UG3 TR004501, by the U.S. National Science Foundation through award NSF CNS-2320261, and by the UIC Institute for Health Data Science Research. We thank the UIC Electronic Visualization Laboratory.

REFERENCES

[1] Eric Ababio Anyimadu, Clifton David Fuller, et al. Collaborative Filtering for the Imputation of Patient Reported Outcomes. In *Database and Expert Sys. Applic.*, pages 231–248. Springer Nature Switzerland, 2024.

[2] Silvia Bauer, Vit Blanar, Jan Pospichal, Doris Eglseer, et al. Association Between Taste Disorders and Malnutrition in Older Adults: A Scoping Review. *Nutrition Reviews*, page nuaf134, 2025.

[3] Charlotte Beaudart, Myriam Zaaria, et al. Health Outcomes of Sarcopenia: A Systematic Review and Meta-Analysis. *PLoS One*, 12(1):e0169548, January 2017.

[4] Kaitlin M Christopherson, Alokananda Ghosh, Abdallah Sherif Radwan Mohamed, Mona Kamal, et al. Chronic radiation-associated dysphagia in oropharyngeal cancer survivors: Towards age-adjusted dose constraints for deglutitive muscles. *Clinical and translational radiation oncology*, 18:16–22, 2019.

[5] Charles S. Cleeland, Tito R. Mendoza, Xin Shelley Wang, Chyi Chou, et al. Assessing symptom distress in cancer patients: The M.D. Anderson Symptom Inventory. *Cancer*, 89:1634—1646, 11 2000.

[6] R. de Bree, M. A. van Beers, and A. W. M. A. Schaeffers. Sarcopenia and its impact in head and neck cancer treatment. *Current Opinion in Otolaryngology & Head and Neck Surgery*, 30(2):87–93, apr 2022.

[7] Federica Dellafiore et al. What is the relations between dysgeusia and alterations of the nutritional status? A metanarrative analysis of integrative review. *Acta Bio Medica: Atenei Parmensis*, 92(Suppl 2):e2021023, 2021.

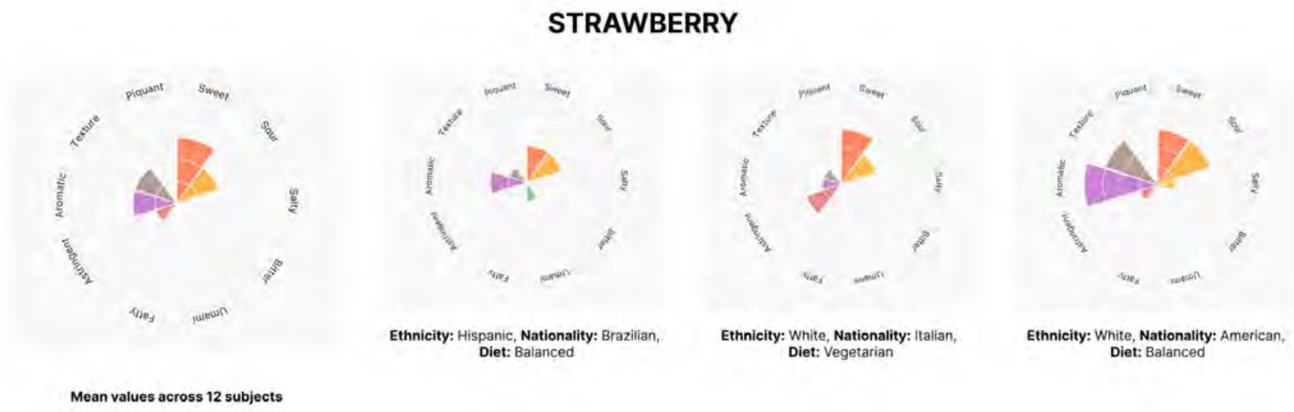

Fig. 6. Strawberry flavor profile mean ratings (twelve respondents), and three individual ratings from different responders, along with the ethnicity, nationality, and diet of each responder.

Fig. 7. Strawberry flavor profile ratings from three at-home responders, along with the ethnicity, nationality, and diet of each responder.

Fig. 8. Tonic Water flavor profile ratings from three at-home responders, along with the ethnicity, nationality, and diet of each responder.

[8] Andrew Dornenburg and Karen Page. *The Flavor Bible: The Essential Guide to Culinary Creativity, Based on the Wisdom of America's Most Imaginative Chefs*. Voracious, 2008.

[9] H Elhalawani, ASR Mohamed, A Kanwar, A Dursteler, et al. Serial Parotid Gland Radiomic-based Model Predicts Post-Radiation Xerostomia in Oropharyngeal Cancer. *Radiotherapy and Oncology*, 127(Suppl. 1):S1167–S1168, 2018.

[10] Joel B Epstein, Gregory Smutzer, and Richard L Doty. Understanding the impact of taste changes in oncology care. *Supportive Care in Cancer*, 24(4):1917–1931, 2016.

[11] Joel B Epstein, Dana Villines, Geena L Epstein, and Gregory Smutzer. Oral examination findings, taste and smell testing during and following head and neck cancer therapy. *Supportive Care in Cancer*, 28(9):4305–4311, 2020.

[12] C. Floricel, A. Wentzel, A. Mohamed, C.D. Fuller, et al. Roses have thorns: Understanding the downside of oncological care delivery through visual analytics and sequential rule mining. *IEEE Trans. Vis. Comp. Graph.*, 30(1), 2024.

[13] Carla Floricel, Nafiul Nipu, et al. THALIS: Human-Machine Analysis of Longitudinal Symptoms in Cancer Therapy. *Trans. Vis. Comp. Graph.*, 28(1):151–161, September 2021.

[14] Alexander J. Grossberg, Surasak Chamchod, et al. Association of Body Composition With Survival and Locoregional Control of Radiotherapy-Treated Head and Neck Squamous Cell Carcinoma. *JAMA Oncology*, 2(6):782–789, jun 2016.

[15] Lucinda Gunn et al. Taste dysfunction following radiotherapy to the head and neck: A systematic review. *Radiotherapy and Oncology*, 157:130–140, 2021.

[16] Caroline Habberstad, Isabel Drake, and Emily Sonestedt. Variation in the sweet taste receptor gene and dietary intake in a swedish middle-aged population. *Frontiers in endocrinology*, 8:348, 2017.

[17] Sara Haydar et al. The Taste Liking Questionnaire (TasteLQ)–A tool for assessment of taste liking in the Danish population. *Food Quality and Preference*, 117, 2024.

[18] Laia Humbert-Vidan, Serageldin Kamel, Andrew Wentzel, et al. Externally validated digital decision support tool for time-to-osteoradionecrosis risk-stratification using right-censored multi-institutional observational cohorts. *Radiotherapy and oncology*, 207, 2025.

[19] S. Kitsiou, M. Thomas, et al. Development of an innovative mHealth platform for remote physical activity monitoring and health coaching of cardiac rehabilitation patients. In *2017 IEEE EMBS Int. Conf. on Biomedical & Health Informatics (BHI)*, pages 133–136, 2017.

[20] Mirko Mantovani, Andrew Wentzel, Juan Trelles Trabucco, Joseph Michaelis, and G Elisabeta_Marai. Kiviat Defense: An Empirical Evaluation of Visual Encoding Effectiveness in Multivariate Data Similarity Detection. *Journal of Imaging Science and Technology*, 67(6), 2023.

[21] G Elisabeta Marai. Activity-centered domain characterization for problem-driven scientific visualization. *Trans. Vis. Comp. Graph.*, 24(1), 2017.

[22] Marco V. Narici and Nicola Maffulli. Sarcopenia: characteristics, mechanisms and functional significance. *British Medical Bulletin*, 95(1):139–159, 03 2010.

[23] Ha M Nguyen, Mary E Reyland, and Linda A Barlow. Mechanisms of taste bud cell loss after head and neck irradiation. *Journal of Neuroscience*, 32(10):3474–3484, 2012.

[24] Nafiul Nipu, Andrew Wentzel, Nasibeh Heshmati, Naveen Kumar Sangi, Xinhua Zhang, Guadalupe Canahuate, C. David Fuller, and G. Elisabeta Marai. mEnergy: Development of a Novel mHealth Multi-device Platform for Near Real-time Remote Assessment of Energy Disorders. In *The 47th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2025.

[25] Samin Nosrat. *Salt, fat, acid, heat: Mastering the elements of good cooking*. Simon and Schuster, 2017.

[26] Marcia Otto and Wes Gibson. Study Reveals Disproportionate Burden of Poor Diet Quality Among Cancer Survivors, with Potential Impact on Cancer Treatment, Disease Progression, Survivorship. https://www.uth.edu/news/story/study-reveals-disproportionate-burden-of-poor-diet-quality-among-cancer-survivors-with-potential-impact-on-cancer-treatment-disease-progression-survivorship, 2025. Accessed: August 29, 2025.

[27] Reddit. A Cool Guide to Everyday Taste Profiles. https://www.reddit.com/r/coolguides/comments/1dxybbv/a_cool_guide_to_everyday_taste_profiles_oc/, 2024. Accessed: August 29, 2025.

[28] Davide Risso, Dennis Drayna, and Gabriella Morini. Alteration, reduction and taste loss: main causes and potential implications on dietary habits. *Nutrients*, 12(11):3284, 2020.

[29] Valter Santilli, Andrea Bernetti, Massimiliano Mangone, and Marco Paoloni. Clinical definition of sarcopenia. *Clinical Cases in Mineral and Bone Metabolism*, 11(3):177–180, Sep 2014.

[30] Giuseppe Sergi, Giulia Bano, Simona Pizzato, Nicola Veronese, et al. Taste loss in the elderly: Possible implications for dietary habits. *Critical reviews in food science and nutrition*, 57(17):3684–3689, 2017.

[31] Tony Sheu, David Vock, Abdallah Mohamed, et al. Conditional survival analysis of patients with locally advanced laryngeal cancer: construction of a dynamic risk model and clinical nomogram. *Scientific reports*, 7(1), 2017.

[32] Simeone Silvio et al. The CiTAS scale for evaluating taste alteration induced by chemotherapy: state of the art on its clinical use. *Acta Bio Medica: Atenei Parmensis*, 90(Suppl 6):17–25, 2019.

[33] Sanjana Srabanti, Michael Tran, et al. A Tale of Two Centers: Visual Exploration of Health Disparities in Cancer Care. In *2022 IEEE 15th Pacific Visualization Symposium (PacificVis)*, pages 101–110, 2022.

[34] Sonja Stieb et al. Prospective observational evaluation of radiation-induced late taste impairment kinetics in oropharyngeal cancer patients: Potential for improvement over time? *Clinical and Translational Radiation Oncology*, 22:98–105, 2020.

[35] Yaohua Wang, Guadalupe M Canahuate, Lisanne V Van Dijk, et al. Predicting late symptoms of head and neck cancer treatment using LSTM and patient reported outcomes. In *Proceedings of the 25th International Database Engineering & Applications Symposium*, pages 273–279, 2021.

[36] Yaohua Wang, Lisanne Van Dijk, Abdallah SR Mohamed, et al. Improving prediction of late symptoms using LSTM and patient-reported outcomes for head and neck cancer patients. In *2023 IEEE 11th International Conference on Healthcare Informatics (ICHI)*, pages 292–300. IEEE, 2023.

[37] A Wentzel, Peter Hanula, et al. Cohort-based T-SSIM visual computing for radiation therapy prediction and exploration. *Trans. Vis. Comp. Graph.*, 26(1), 2019.

[38] Andrew Wentzel, Serageldin Attia, Xinhua Zhang, et al. Ditto: A visual digital twin for interventions and temporal treatment outcomes in head and neck cancer. *Trans. Vis. Comp. Graph.*, 2024.

[39] Andrew Wentzel, Carla Floricel, Guadalupe Canahuate, et al. DASS Good: Explainable Data Mining of Spatial Cohort Data. *Comp. Graph. For.*, 24(3), 2023.

[40] Andrew Wentzel, Peter Hanula, Lisanne V van Dijk, et al. Precision toxicity correlates of tumor spatial proximity to organs at risk in cancer patients receiving intensity-modulated radiotherapy. *Radiotherapy and Onc.*, 148, 2020.

[41] Andrew Wentzel, Timothy Luciani, Lisanne V. van Dijk, et al. Precision association of lymphatic disease spread with radiation-associated toxicity in oropharyngeal squamous carcinomas. *Radiotherapy & Onco.*, 161, 2021.

[42] Andrew Wentzel, Abdallah S. R. Mohamed, Mohamed A. Naser, et al. Multi-organ spatial stratification of 3-d dose distributions improves risk prediction of long-term self-reported severe symptoms in oropharyngeal cancer patients receiving radiotherapy: development of a pre-treatment decision support tool. *Front. in onc.*, 13, 2023.

[43] Luka Zdilar, David M Vock, G Elisabeta Marai, et al. Evaluating the effect of right-censored end point transformation for radiomic feature selection of data from patients with oropharyngeal cancer. *JCO clinical cancer informatics*, 2:1–19, 2018.