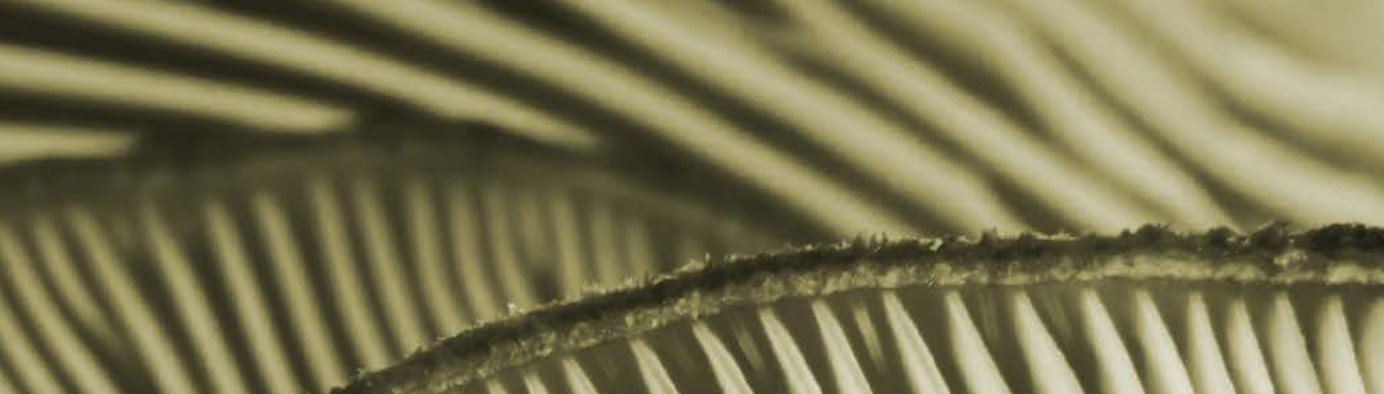




IntechOpen

IntechOpen Series
Food Science and Nutrition, Volume 22

Sensory Analysis in Food Science

Integration of Emo-Sensory Studies,
Sensory Tests, and Artificial Intelligence

Edited by Alice Vilela



Sensory Analysis in Food Science - Integration of Emo-Sensory Studies, Sensory Tests, and Artificial Intelligence

Edited by Alice Vilela

Published in London, United Kingdom

Sensory Analysis in Food Science – Integration of Emo-Sensory Studies, Sensory Tests, and Artificial Intelligence

<http://dx.doi.org/10.5772/intechopen.1008090>

Edited by Alice Vilela

Contributors

Alice Vilela, Amparo Eccoña-Sota, Bianca Pio Ávila, Catarina Marques, Ennet Moholisa, Gianni Corino, Gulcan Koyuncu, Jie Yan, Kealeboga Mosimanyana, Layla Damé Macedo, Lizelle Rheeders, Mutita Meenune, Márcia Arocha Gulate, Nicodemo Crescencio Jamanca-Gonzales, Phillip Strydom, Reynaldo Justino Silva-Paz, Sittiwat Lertsiri, Thalia Alexandra Rivera-Ashqui, Wilatsana Posri

© The Editor(s) and the Author(s) 2026

The rights of the editor(s) and the author(s) have been asserted in accordance with the Copyright, Designs and Patents Act 1988. All rights to the book as a whole are reserved by INTECHOPEN LIMITED. The book as a whole (compilation) cannot be reproduced, distributed or used for commercial or non-commercial purposes without INTECHOPEN LIMITED's written permission. Enquiries concerning the use of the book should be directed to INTECHOPEN LIMITED rights and permissions department (permissions@intechopen.com).

Violations are liable to prosecution under the governing Copyright Law.



Individual chapters of this publication are distributed under the terms of the Creative Commons Attribution 4.0 License which permits commercial use, distribution and reproduction of the individual chapters, provided the original author(s) and source publication are appropriately acknowledged. If so indicated, certain images may not be included under the Creative Commons license. In such cases users will need to obtain permission from the license holder to reproduce the material. More details and guidelines concerning content reuse and adaptation can be found at <http://www.intechopen.com/copyright-policy.html>.

Notice

Statements and opinions expressed in the chapters are those of the individual contributors and not necessarily those of the editors or publisher. No responsibility is accepted for the accuracy of information contained in the published chapters. The publisher assumes no responsibility for any damage or injury to persons or property arising out of the use of any materials, instructions, methods or ideas contained in the book.

First published in London, United Kingdom, 2026 by IntechOpen

IntechOpen is the global imprint of INTECHOPEN LIMITED, registered in England and Wales, registration number: 11086078, 167-169 Great Portland Street, London, W1W 5PF, United Kingdom

For EU product safety concerns: IN TECH d.o.o., Prolaz Marije Krucifikse Kozulić 3, 51000 Rijeka, Croatia, info@intechopen.com or visit our website at intechopen.com.

British Library Cataloguing-in-Publication Data

A catalogue record for this book is available from the British Library

Sensory Analysis in Food Science – Integration of Emo-Sensory Studies, Sensory Tests, and Artificial Intelligence

Edited by Alice Vilela

p. cm.

This title is part of the Food Science and Nutrition Book Series, Volume 22

Topic: Food Chemistry

Series Editor: Maria Rosário Bronze

Topic Editor: Thuan-Chew Tan

Print ISBN 978-1-83635-379-9

Online ISBN 978-1-83635-378-2

eBook (PDF) ISBN 978-1-83635-380-5

ISSN 2977-8174

If disposing of this product, please recycle the paper responsibly.

IntechOpen Book Series

Food Science and Nutrition

Volume 22

Aims and Scope of the Series

The significance of food is undeniable, especially in light of the impending challenge facing humanity: ensuring there will be enough food to meet the basic needs of a population expected to reach approximately 10 billion by 2050. These food-related challenges align with some of the United Nations' sustainable development goals, with a target to achieve them by 2030. One thing is certain: food should be not only nourishing and safe but also tailored to the diverse needs of individuals throughout their lifetimes, all while meeting consumers' sensory expectations. Understanding the diverse chemical composition of food, often referred to as biodiversity, and how these components can contribute to human health by considering factors like bioaccessibility, bioavailability, and bioactivity at the organ level, is crucial for grasping and promoting a healthy diet. Thanks to the continuous evolution of analytical methods and interdisciplinary research, significant strides have been made in the field of food science and nutrition.

Meet the Series Editor



Maria Rosário Bronze has been working in Analytical Chemistry since 1986. Her Ph.D. in 1999 contributed to the study of food products using capillary electrophoresis. The main goal of her research since 1999 has been focused on Analytical Chemistry applied mainly to the analysis of foods and by-products of food industry. She conducted research in collaboration with national and international research groups, at iBET and ITQB Technology Division. From 2017 until 2021 she was head of Food & Health Division at iBET and head of the Food Functionality and Bioactives Laboratory. MR Bronze has been an Associate Professor at the Pharmacy Faculty of Lisbon University and head of the Structural Analysis Laboratory since 2012. As a researcher, MR Bronze is a Senior Scientific Advisor at Food & Health Division at iBET and Head of Food Functionality and Bioactives Laboratory at the same Institute, Collaborator at iMED and Researcher at ITQB NOVA. Her current research is focused on quality and beneficial health effects of food components. Gas and liquid chromatography associated with mass spectrometry are used by MR Bronze in the characterization of samples. Sensory evaluation is also an important area of her research. The main food products studied by her are olive tree products (olive, olive oil, leaves), cereals such as maize, legumes (faba bean, pea, chickpea, lentils) fruits (apple, grapes, opuntia ficus), fruit juices and wine, among others. More recently her interests have also involved biodiversity, bioaccessibility, and bioavailability studies on food products and their components, mainly phytochemicals as phenolic compounds, using different analytical tools such as mass spectrometry. As a senior scientific advisor at Food & Health Division at iBET she is involved in different areas: (i) isolation, characterization and formulation of bioactive and functional compounds or extracts from natural sources and wastes from food and other related industries; (ii) pre-clinical assays to provide support to understand health claims related with the beneficial effects of food nutrients/bioactive components; (iii) establishment of analytical methodologies including mass spectrometry state-of-the-art to fully characterize different matrices, from food products, natural extracts or biological fluids (Food Functionality and Bioactives Laboratory).

Meet the Volume Editor



Alice Vilela has a degree in Enology, a Master's degree in Genetics and Species Improvement, and a Ph.D. in Microbiology from UTAD. She began her teaching career at UTAD in 1999 and is currently an Assistant Professor in the Department of Agronomy at the School of Agricultural and Veterinary Sciences (ECAV). Her teaching experience encompasses undergraduate, master's, and doctoral courses. She serves as the head of several curricular units and advises students across three teaching cycles. She is involved in university management activities, holding leadership positions as Director of the Master's Degree in Oenology and Viticulture and Vice-Director of the Bachelor's Degree in Oenology. She is the Director of the UTAD Tasters panel. Actively participates in disseminating knowledge, organizing, and participating in international and national events, as well as university extension activities within and outside Portugal. Participated in more than 20 strategic projects with competitive financing and national and global partnerships. Her research focuses on the bioreduction of volatile acidity in wines, biodealcoholization of wines, sensory evaluation of food and wines, and development of sensory tests. She has published more than 95 articles in international scientific journals, 14 technical articles, 24 book chapters, and over 120 conference proceedings publications. Her h-index is currently 28. She is an active reviewer for several SCI journals, including Food Research International, Journal of the Science of Food and Agriculture, Food Chemistry, Journal of Gastronomy and Food Science, and several MDPI journals (Foods, Fermentation, Beverages, and Molecules). Additionally, she serves as an Academic Editor and is a member of the Editorial Board of several SCI journals. From 2021 to 2024, Stanford University, USA, recognized her as one of the world's top 2% most cited scientists.

Contents

Preface	XIII
Chapter 1 Emo-Sensory Profiling in Foods and Wine <i>by Catarina Marques and Alice Vilela</i>	1
Chapter 2 Consumers' Acceptability and Purchase Intent of Cow Blood Sausage in South African Ethnic Groups <i>by Ennet Moholisa, Lizelle Rheeders, Kealeboga Mosimanyana and Phillip Strydom</i>	21
Chapter 3 The Future of Diets with Customized Sensory Cues <i>by Jie Yan and Gianni Corino</i>	33
Chapter 4 Food Flavour Perception and the Measurement of Tastes and Smells <i>by Sittiwat Lertsiri, Mutita Meenune and Wilatsana Posri</i>	53
Chapter 5 Sensory Analysis Methods and Quality Characteristics of Foods <i>by Gulcan Koyuncu</i>	71
Chapter 6 Rapid Descriptive Methodologies in Food Sensory Analysis: CATA, Free Choice Profile and Flash Profile <i>by Reynaldo Justino Silva-Paz, Nicodemo Crescencio Jamanca-Gonzales, Thalia Alexandra Rivera-Ashqui and Amparo Eccoña-Sota</i>	87
Chapter 7 Perspective Chapter: Sensory Lifetime Optimization Using Artificial Intelligence <i>by Bianca Pio Ávila, Layla Damé Macedo and Márcia Arocha Gularte</i>	103

Preface

Sensory analysis plays a huge role in product development, quality control, and consumer research within the food industry. It provides a scientific framework to translate subjective human perceptions into objective, quantifiable data. With the evolution of consumer-centered approaches, the scope of sensory analysis has expanded beyond traditional attribute-based testing to explore the emotional and psychological dimensions of food experience.

Classical sensory evaluation employs descriptive analysis, discrimination tests, and affective tests to assess specific sensory attributes or consumer preferences. Descriptive analysis, often conducted by trained panels, identifies and quantifies sensory characteristics, whereas affective tests measure consumer liking and preference. Emerging methodologies now integrate physiological measurements, such as facial expression analysis and heart rate monitoring, to capture implicit emotional responses during food consumption.

Emo-sensory studies represent a convergence between sensory science and affective psychology, focusing on the emotional reactions elicited by sensory stimuli. Emotions play a crucial role in shaping food choice, satisfaction, and long-term consumer loyalty. Tools such as the FeceReader® enable researchers to map the emotional landscape associated with food experiences. Additionally, advances in biometric technologies and neuroscientific tools, including EEG and eye-tracking, provide objective insights into the emotional and cognitive aspects of sensory perception.

Artificial intelligence has become a transformative force in sensory analysis, offering sophisticated data modeling and predictive capabilities. Machine learning algorithms can process complex, multidimensional sensory and consumer data to identify patterns, predict consumer acceptance, and optimize product formulations. In emo-sensory research, AI facilitates real-time emotion recognition through image and voice analysis, enabling automated assessment of emotional responses during sensory tests. Furthermore, deep learning models are increasingly employed to simulate sensory perceptions, predict sensory quality from chemical and instrumental data, and support virtual product development through digital twins.

The integration of sensory science, emo-sensory approaches, and AI opens new frontiers for understanding human–food interactions. In the future, the development of hybrid sensory systems that combine human sensory input with computational intelligence holds promise for creating more personalized, emotionally resonant, and sustainable food products. Ethical considerations, data privacy, and the need for standardized methodologies remain critical challenges. Future research will likely focus on multimodal data fusion, real-time consumer feedback, and the development of AI systems capable of emulating human sensory judgments.

Sensory analysis is undergoing a profound transformation driven by the incorporation of emotional and computational dimensions. The synergy among traditional sensory evaluation, emotion-sensory studies, and artificial intelligence enriches scientific understanding of consumer experience, enhances product innovation, and supports evidence-based decision-making in the food industry. As AI technologies continue to evolve, they are poised to redefine the methodological and conceptual boundaries of sensory science.

This book explores the conceptual and methodological intersections between sensory analysis, emo-sensory studies, and AI-driven data processing, highlighting the emergence of intelligent sensory systems in modern food research.

Alice Vilela
CQ-VR – Chemistry Research Centre,
Department of Agronomy,
University of Trás-os-Montes e Alto Douro,
Vila Real, Portugal

Emo-Sensory Profiling in Foods and Wine

Catarina Marques and Alice Vilela

Abstract

Emo-sensory profiling represents an emerging multidisciplinary approach within sensory and consumer science, exploring the emotional responses elicited by the sensory characteristics of foods and beverages, particularly wine. Moving beyond traditional sensory analysis focused on hedonic attributes, emo-sensory profiling integrates emotional dimensions into the evaluation of consumer experiences. This chapter outlines the theoretical foundations and key methodologies of emo-sensory profiling, including tools such as emotion lexicons, emoji-based scales, and facial expression recognition software, such as FaceReader. One case study on Douro wines illustrates how emotional responses vary across wine types and consumer demographics, with findings showing that women displayed higher emotional arousal and that Port wines evoked stronger surprise reactions. This review demonstrates that emotion-based profiling enables more effective consumer segmentation than hedonic scales and enhances innovation in marketing and product design, particularly in immersive wine tourism experiences supported by virtual reality. Furthermore, the integration of psychophysiological and digital tools allows for a more comprehensive understanding of the multisensory emotional landscape of food and wine. Taken together, these insights show how emo-sensory profiling can serve as a strategic tool for aligning product attributes with emotional engagement, thus advancing consumer-centered innovation in the agri-food and wine sectors.

Keywords: consumers' expectations, emotion lexicons, emoji-based scales, physiological measurements, FaceReader

1. Introduction

Food and wine sensory analysis examines how consumers perceive, evaluate, and appreciate food and wine, focusing on the interplay between sensory attributes, consumer expectations, and overall pleasantness. Understanding these factors enables producers and marketers to tailor products and experiences that better meet consumer preferences and enhance overall satisfaction.

Consumers prefer wines with low bitterness, heat, metallic, smoky, and peppery notes. Positive drivers include red berry, floral, caramel, and vanilla aromas, as well as balanced acidity and astringency. These sensory attributes often outweigh varietal differences in determining liking [1, 2].

Appropriate pairings are associated with increased liking, sensory complexity, and higher expected price, especially when wine dominates the pairing. However, the increase in liking is more pronounced for the wine than the food component [3, 4]. Consumers favor sweet, sour, and balanced fragrances for fruit wines, while bitterness, astringency, and medicinal notes are disliked. Sensory characteristics, mainly taste and aroma, are the main factors influencing preference [1].

Label colors and sensory descriptions strongly shape consumer expectations before tasting. For example, red and black labels evoke expectations of tangy flavors, while red and orange suggest fruity and floral notes. Frequent buyers have stronger expectations based on label cues [5, 6]. Organic labels and provenance information can also enhance perceived sensory quality, pleasantness, and purchase intention, mediated by increased sensory ratings and perceived healthiness. However, the context of dining and individual health concerns can moderate these effects [4, 7].

The pleasantness of food and wine consumption can be measured directly (e.g., liking scores, balance, and appropriateness) or indirectly (e.g., sensory complexity, hedonic valence of sensory terms). Both approaches are moderately correlated and can be used to predict consumer preferences [3, 8]. Fine wines are often rated as more complex and persistent; however, they may elicit unpleasant emotions and lower overall liking compared to young, fruity wines, highlighting a disconnect between expert and consumer evaluations [2, 9].

Different consumer segments have distinct sensory preferences and responses to sensory cues. Segmenting consumers by their preferences or attitudes (e.g., health interest and wine usage frequency) helps explain variability in liking and expectations [1, 3, 6]. There is often a lack of alignment between expert quality ratings and consumer liking, highlighting the importance of consumer-focused sensory analysis [2, 10].

This chapter aims to (i) provide a comprehensive overview of the theoretical and methodological foundations of emo-sensory profiling in the context of food and wine; (ii) highlight its practical applications through a case study involving the emotional responses to Douro wines using FaceReader software; and (iii) discuss the broader implications, current challenges, and future opportunities for integrating emo-sensory tools into product development, experiential marketing, and consumer research in the agri-food and wine sectors.

2. Theoretical and multidisciplinary foundations of emo-sensory profiling in food and wine

Emo-sensory profiling emerges at the crossroads of sensory science, psychology, neuroscience, and marketing, offering a multidisciplinary lens to understand how foods and beverages can evoke complex emotional responses. Over time, these have been complemented by faster and more holistic techniques, such as Check-All-That-Apply (CATA), Napping (N), Flash Profile (FP), and Temporal Dominance of Sensations (TDS), which, when combined with appropriate statistical analyses, are crucial for product development and acceptance. However, sensory attributes alone cannot fully explain consumer acceptance [11]. This evolving field expands the evaluative framework to encompass emotional and mnemonic aspects that shape the consumer experience.

Sensory perception is inherently emotional. Recent advances have shown that taste, aroma, texture, and visual cues can activate affective responses through both conscious associations and unconscious physiological mechanisms. Studies have

demonstrated that olfactory and gustatory stimuli modulate emotional states and are tightly linked to memory circuits in the brain, particularly those involving the amygdala and hippocampus [11–14]. This is particularly salient in wine, where complex sensory cues often trigger autobiographical memories and mood-related associations. For example, emotional profiling tools such as FaceReader and emoji-based scales have been applied to Douro wines to decode facial expressions and emotional responses linked to terroir differences, suggesting that regional identity can be sensorially and emotionally perceived [15].

From a psychological perspective, emotion and memory are central to food experiences. The associative and affective processes behind food consumption contribute to both immediate perception and long-term preference. Emotional reactions to specific foods or wines can be shaped by early-life exposure, cultural background, or even a memorable event. Neuroscientific insights have shown that these associations are encoded through multisensory integration processes, with somatosensory, olfactory, and visual signals converging in brain areas responsible for emotional valuation and memory recall [16].

Recent work has highlighted the interplay between subjective reports, physiological measures, and biological predispositions in shaping emotional responses to taste and smell. In a comprehensive review, Mastinu et al. [17] examined how emotional reactions to flavor stimuli can be assessed through self-reported tools and psychophysiological indicators (e.g., heart rate and skin conductance), revealing significant individual variability. Their findings suggest that psychological traits and genetic differences, such as variations in taste receptor genes, may influence how individuals emotionally perceive and process sensory information. This reinforces the complexity of emo-sensory profiling and underscores the importance of integrative methodologies that account for both objective and subjective dimensions of experience.

Recent research has also emphasized the role of context and environment. Multisensory design, encompassing visual esthetics, ambient lighting, soundscapes, and tactile elements such as packaging or glassware, has been demonstrated to influence the emotional tone and flavor perception [16, 18, 19]. For instance, virtual reality and digital tools have opened new avenues for immersive sensory evaluation, allowing researchers to study emotional responses in more ecologically valid or fantastical settings [20]. These innovations reflect a growing emphasis on experience-driven consumption and the need for sensory methodologies that can effectively capture and integrate complexity.

In parallel, applied sensory science has begun to embrace these frameworks. Studies on wine, wine-related products, and vinegar have revealed that emotional dimensions are closely linked to sensory characteristics, chemical composition, and bioactive content. For instance, Port wine vinegars have been shown to carry sensory depth and emotional appeal, offering new opportunities for product diversification and storytelling [21].

Marketing and consumer sciences have leveraged emotional and sensory insights to enhance emotional branding and develop targeted products. Emotion-based profiling has shown greater effectiveness than traditional hedonic scales in guiding product innovation, enabling more nuanced consumer segmentation, supporting value-added claims, and enhancing immersive wine tourism experiences, as demonstrated in recent applications of emoji-based scales, facial expression analysis, and VR-enhanced tasting environments [20, 22–25]. Digital platforms, AI-driven emotion recognition, and advanced sensory assessment have been increasingly incorporated into sensory studies and marketing strategies [22, 26].

Together, these developments emphasize the integrative potential of emo-sensory assessment. Drawing on neuroscience, psychology, sensory analysis, and marketing, this approach provides a nuanced understanding of how people perceive and emotionally engage with food and wine. It opens new frontiers for research and innovation, ranging from personalized nutrition and well-being to the design of engaging, emotionally resonant food experiences.

3. Methodologies of emo-sensory profiling

Emo-sensory profiling methods have undergone significant evolution, reflecting advances in sensory science, psychophysiology, and digital technologies. Initially grounded in classical descriptive methods such as hedonic scales and quantitative descriptive analysis (QDA), these approaches have been enriched with tools that capture explicit and implicit emotional responses [26]. A comprehensive review by Kaneko et al. [27] highlights the diversity of methods used to evaluate food-evoked emotions, including explicit approaches such as verbal and pictorial scales, as well as implicit techniques based on physiological responses and facial expression analysis. Explicit methods include verbal, pictorial, and symbolic scales, such as the EmoSensory® wheel and the EmojiGrid (Figure 1), which allow consumers to express feelings associated with food and beverage experiences in accessible and cross-linguistic ways. These techniques have been successfully applied to studies of wine, chocolate, and coffee, yielding emotional profiles that correlate with specific sensory attributes [28].

On the other hand, implicit methods are gaining prominence by revealing involuntary emotional dimensions through psychophysiological indicators, such as heart rate [27], skin conductance [27], facial temperature [30], and facial expressions analyzed using software like FaceReader [15]. These measures provide

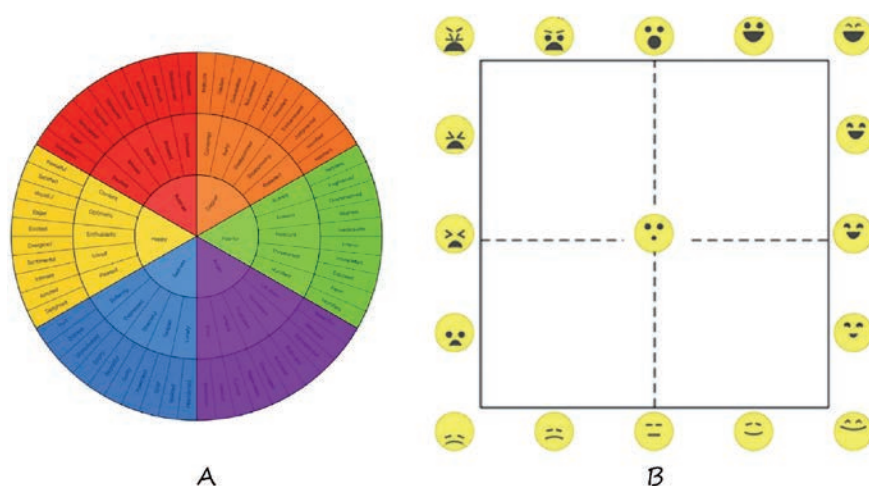


Figure 1.

A – The EmoSensory® Wheel, created by Schouteten et al. [28] to obtain both an emotional and sensory profile for food products using a hands-on consumer method; B – The EmojiGrid, an emoji-based Affect Grid designed to measure food-related feelings. It features facial expressions ranging from dislike (unpleasant) to like (pleasant) on the horizontal valence axis, while intensity increases vertically on the arousal axis, as retrieved from Kaneko et al. [29].

objective data on affective engagement, even when participants do not verbalize their reactions. Recent studies have combined autonomic response data and facial expressions with aroma chemical descriptors, allowing researchers to correlate specific volatile compounds with emotional response patterns during wine tasting [23, 31].

The use of multimodal approaches, integrating self-report tools with physiological and biometric data, represents a well-established trend. This type of multi-channel analysis offers a more comprehensive understanding of the sensory experience, bridging subjective and objective dimensions of emotion [24, 32]. Emerging technologies such as virtual reality (VR) and artificial intelligence (AI) are increasingly incorporated into evaluation methodologies, enabling immersive and ecologically valid settings that modulate both sensory perception and emotional response [20, 33]. Recent research suggests immersive environments can significantly influence sensory appreciation and emotional states elicited by food and beverage consumption [25, 33, 34].

To illustrate the diversity of techniques currently used in this field, **Table 1** summarizes key methodologies employed in emo-sensory profiling. It distinguishes

Method type	Specific methods/tools	Description	References
Explicit	Hedonic scales, QDA (quantitative descriptive analysis)	Classical sensory methods capture conscious preferences and descriptive attributes.	[26]
Explicit	Verbal, pictorial, and symbolic scales (e.g., EmoSensory® wheel, EmojiGrid)	Allow consumers to express emotions explicitly; cross-cultural applicability.	[27, 28]
Implicit	Heart rate, skin conductance, facial temperature	Psychophysiological indicators of involuntary emotional reactions.	[27, 30]
Implicit	Facial expression analysis (e.g., FaceReader software)	Detects subtle emotional cues through automatic analysis of facial muscle movements.	[15]
Multimodal	Combination of explicit self-reports and biometric/physiological measures	Enables comprehensive emotional profiling by merging subjective and objective data.	[24, 32]
Chemosensory + emotion	Correlation of aroma compounds with emotional responses	Links volatile composition to specific emotional reactions, especially in wine studies.	[28, 29]
Technological	Virtual reality (VR)	Creates immersive environments that enhance the ecological validity of testing conditions.	[20, 33]
Technological	Artificial Intelligence (AI)	Supports data integration and advanced analysis of complex emotion-sensory datasets.	[33]
Ecological approaches	Immersive environments for food and beverage testing	Modulate emotional and sensory responses to provide context-rich and realistic consumption experiences.	[25, 34]

Table 1.
Summary table with methodologies of emo-sensory profiling.

between explicit and implicit approaches, highlighting their primary applications in food and wine research.

Therefore, contemporary emo-sensory profiling is characterized by an integrative approach in which technological and biometric tools complement traditional sensory methods. This approach accurately explains how consumers experience food products across multiple sensory and emotional dimensions.

To further clarify the multi-step methodology behind emo-sensory profiling, **Figure 2** presents a schematic workflow that outlines the main stages of the process.

To enhance methodological clarity, **Table 2** presents a comparative overview of major emo-sensory approaches, including both explicit and implicit tools. Each method is evaluated in terms of key reference(s), main strengths, typical applications, and known limitations. This table complements **Table 1** by enabling readers to understand the trade-offs between techniques better and guide appropriate methodological choices, depending on study goals, the product matrix, and the target population.

Furthermore, future research directions should prioritize the exploration of dynamic tasting environments, such as immersive virtual reality (VR) settings, to examine how multisensory context modulates emotional responses. Another critical avenue involves the development of machine learning models capable of integrating chemical composition, sensory descriptors, and biometric data (e.g., facial expressions and physiological signals) for predictive emo-sensory profiling. Ultimately,

Workflow for Emo-Sensory Profiling

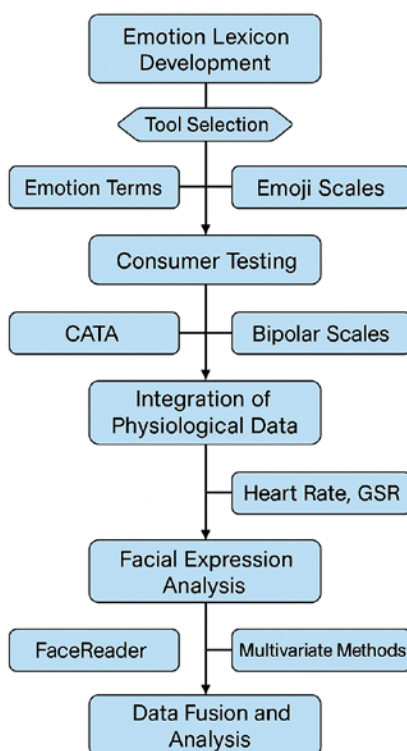


Figure 2.
Workflow for emo-sensory profiling.

Method	Ref.	Strengths	Applications	Limitations
CATA (Check-All-That-Apply)	[28]	Simple, intuitive, cross-cultural; suitable for emotion-word elicitation	Rapid consumer tests, emotional profiling in foods	Limited depth; relies on verbal literacy and consumer memory
Bipolar scales (e.g., valence–arousal)	[29]	Captures emotional intensity and polarity; easy to implement	Hedonic/emotional mapping of food and wine	May oversimplify emotions; less effective for subtle differences
Physiological measures	[17, 27]	Objective, involuntary indicators of emotion (e.g., HR and GSR)	Implicit affective response tracking	Requires technical setup; influenced by extraneous variables
Facial expression recognition (FaceReader)	[15]	Real-time, non-invasive; captures subtle emotional cues	Wine tasting, sensory tourism, consumer segmentation	Sensitive to lighting and camera angle; privacy concerns
Hybrid protocols (Multimodal)	[24, 35]	Comprehensive view; integrates subjective and objective data	Predictive profiling, personalized product development	High complexity; requires advanced data analysis expertise

Table 2.
Comparative overview of major emo-sensory profiling approaches.

longitudinal studies examining the impact of repeated exposure or wine aging on emotional engagement can provide valuable insights into the temporal evolution of consumer perception and affective memory.

4. Practical applications of emo-sensory profiling

Emo-sensory profiling has become increasingly relevant in practical contexts such as product development, quality control, sensory marketing, and tourism experiences, offering powerful insights into consumer engagement. The following table (**Table 3**) summarizes practical examples of how emo-sensory profiling is applied across different sectors, illustrating its versatility and growing relevance.

In food and wine product innovation, emotional profiling enables the identification of sensory-emotional signatures that resonate with specific consumer segments, informing the formulation of emotionally engaging products [28, 33]. For instance, specific aroma profiles in red wine have been associated with feelings of comfort and familiarity, guiding the blending or aging processes to evoke targeted emotional responses [36].

In marketing and branding, emo-sensory data supports the creation of emotionally charged narratives and packaging strategies. Emotional mapping of food and beverages allows brands to align product communication with consumer expectations and emotional needs [22]. Recent applications include the use of emoji-based scales and facial expression analysis to tailor promotional campaigns and packaging design based on elicited affective states [23].

In sensory tourism and experiential marketing, particularly within wine tourism, emo-sensory tools have been used to design multisensory tasting rooms and immersive environments that enhance emotional resonance. Virtual and augmented reality are increasingly employed to simulate vineyard landscapes or production processes,

Application area	Practical example	References
Product development	Emotional profiling is used to identify sensory-emotional signatures (e.g., comfort from red wine aromas) to guide product formulation.	[28, 33, 36]
Marketing and branding	Design emotionally resonant packaging and campaigns using emoji scales and facial expression analysis.	[22, 23]
Sensory tourism and experiential marketing	Implementation of VR/AR tasting rooms simulating vineyard landscapes to enhance emotional connection to terroir.	[20, 25]
Digital platforms and E-commerce	Use apps and AI to predict emotional responses and remotely personalize product recommendations.	[24]
Public health and well-being	Encouraging healthy food choices through emotionally positive experiences, with applications in children's and elderly nutrition.	[32]
Therapeutic settings	Using aroma and texture to evoke comfort in patients with neurodegenerative or mental health conditions.	[19]
Sustainability and innovation	Linking emotional appeal with sustainability (e.g., consumer appreciation for vinegars from wine residues).	[21]

Table 3.
Practical applications of emo-sensory profiling.

deepening the emotional connection between consumers and terroir [20, 25]. These approaches enrich storytelling and elevate perceived value, particularly in premium wine segments.

Moreover, emo-sensory profiling is being integrated into digital platforms to enable remote sensory evaluations and emotion-driven product recommendations. Apps and AI-based systems can predict emotional reactions to particular food and beverage profiles, supporting personalized nutrition and enhancing online shopping experiences [24]. These innovations are especially valuable in contexts with limited traditional in-person sensory panels.

In public health and well-being, emotion-based profiling contributes to interventions designed to improve food choices. For instance, emotionally positive experiences with healthy foods may increase acceptance and habitual consumption, particularly among children and older adults [32]. Emotional profiling has also shown potential in therapeutic settings, where sensory stimuli such as aroma and texture evoke comforting emotional states in patients with neurodegenerative diseases or mental health challenges [19].

Finally, the agri-food and wine industries are beginning to adopt emo-sensory strategies for sustainability-oriented innovation. Producers can foster stronger emotional connections with eco-conscious consumers by aligning emotional appeal with sustainability narratives. Studies have shown that emotional engagement can influence perceptions of quality and value, even for upcycled or unconventional products such as vinegars derived from wine residues [21].

4.1 A case study on FaceReader software

Facial expression analysis software, specifically FaceReader, has become a powerful tool in applying emo-sensory profiling because it provides objective, real-time assessments of consumers' emotional responses during food and beverage

consumption. FaceReader utilizes computer vision and machine learning algorithms to detect subtle facial muscle movements and classify emotions, including happiness, sadness, anger, surprise, fear, and disgust [15]. This capability enables researchers to access involuntary emotional reactions that participants may not consciously express or articulate verbally.

FaceReader has played a crucial role in decoding complex emotional responses associated with sensory experiences and regional identity in the context of wine and related products. For instance, recent studies on Douro wines demonstrated how facial emotion recognition can reveal nuanced differences in consumer reactions to terroir-driven sensory profiles, uncovering emotional signatures that align with the wines' geographical and cultural attributes [15, 31]. This goes beyond traditional sensory descriptive data, bridging sensory perception with affective engagement.

Figure 3 illustrates the emotions detected on FaceReader and during the tasting of Douro wines in the Marques and Vilela [15] study.

In the study by Marques and Vilela [15] and Marques et al. [31] on using FaceReader software, version 9.0 (Noldus Information Technology, Wageningen, The Netherlands), to gain insights into emotional responses elicited by different Douro wines, participants were strategically positioned about 1 meter away from a Samsung mobile phone. This phone captured their facial expressions against a plain white background with optimal lighting conditions. During the tasting and recording session, participants were instructed to refrain from speaking and to minimize any unnecessary movements that could interfere with the measurements, ensuring a clear, frontal view of their faces.

Approximately 25 mL was poured into a 21.5 cl ISO tasting glass for each wine sample, adhering to the ISO 3591 standard established in 1977 [38]. Participants then tasted the wine, and video recordings commenced, lasting 10–20 seconds for each sample. The recordings were made at 2160 × 3840 (UHD) resolution, ensuring high-definition footage for subsequent analysis. This standardized approach facilitated

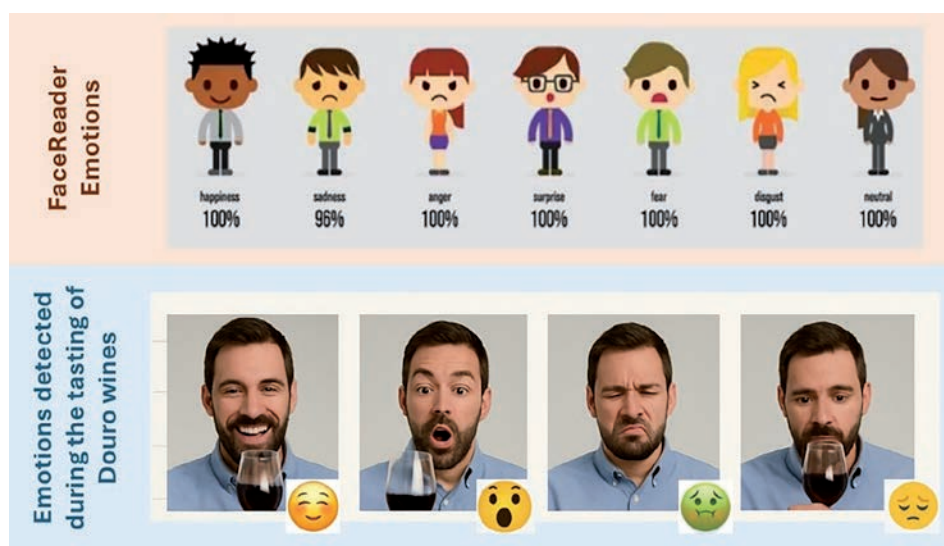


Figure 3. Emotions detected during the tasting of Douro wines using FaceReader software. Adapted from Marques and Vilela [15]; Loijens and Krips [37].

consistent and controlled documentation of participants' facial reactions while tasting the wine, allowing for the collection of a comprehensive dataset that could be further examined using a facial expression reader [15, 31].

For video analysis, the basic version of the program was utilized, employing the default face model and a sample rate set to capture every frame. Subsequently, an EXCEL file containing the quantified emotions was generated [15, 31].

The data analysis process was conducted in three distinct stages, as outlined by Wijk et al. [39]. The initial stage involved face detection, which is essential for modeling facial expressions. A classification phase utilized an artificial neural network to categorize the various expressions. This classification enabled the measurement of fundamental emotions—specifically happiness, sadness, anger, surprise, fear, disgust, contempt, and neutrality. Each emotion was quantified on a scale from 0 to 1, where 0 indicates no emotion detection and 1 signifies the maximum detection level.

The mentioned works [15, 31] have shown that different types of wines can evoke a diverse range of emotions in consumers. White wines, for instance, tend to elicit a broader emotional spectrum, with sadness often arising due to their higher acidity levels. In contrast, red wines are often associated with less sadness, likely due to their richer and fuller-bodied characteristics. Port wines, renowned for their distinctive characteristics, often surprise tasters, suggesting that the type of wine has a significant impact on emotional reactions.

Furthermore, an analysis of arousal levels revealed that female participants exhibited consistently higher arousal across all wine samples than their male counterparts. This finding suggests that women may be more sensitive to the tasting experience because they are more attuned to subtle flavor nuances or more expressive emotional responses. These gender differences highlight the importance of considering demographic factors in sensory evaluations [15].

Utilizing Principal Component Analysis (PCA), **Figure 4**, researchers categorized wines based on the emotions they elicit, revealing distinct emotional experiences linked to white, red, and Port wines. This analysis reinforces the significant role of the wine type in shaping emotional responses and opens up avenues for marketing and product development. Tailoring wine offerings to evoke specific emotional reactions could enhance consumer satisfaction and engagement [15].

Applied to product innovation, this technology identifies emotional drivers that contribute to consumer preference and loyalty. By integrating facial emotion data with sensory descriptive analysis and chemical profiling, researchers can map specific volatile compounds or flavor notes to emotional reactions, providing actionable insights for product formulation and marketing [23].

Moreover, FaceReader's non-invasive and rapid assessment method facilitates its use in diverse settings, from controlled laboratory tastings to more dynamic environments such as sensory tourism events or retail spaces. However, the effective deployment of FaceReader requires attention to environmental factors, such as lighting and camera positioning, participant variability, and ethical considerations surrounding privacy and data security [15, 40].

Despite these challenges, integrating FaceReader into multi-modal emo-sensory approaches enhances the robustness of emotional profiling. When combined with explicit self-report scales and physiological measures, such as heart rate or skin conductance, it contributes to a comprehensive understanding of consumer experience that captures both conscious and unconscious emotional layers.

The use of FaceReader exemplifies the practical application of advanced technologies in emo-sensory profiling, reinforcing the paradigm shift toward data-driven,

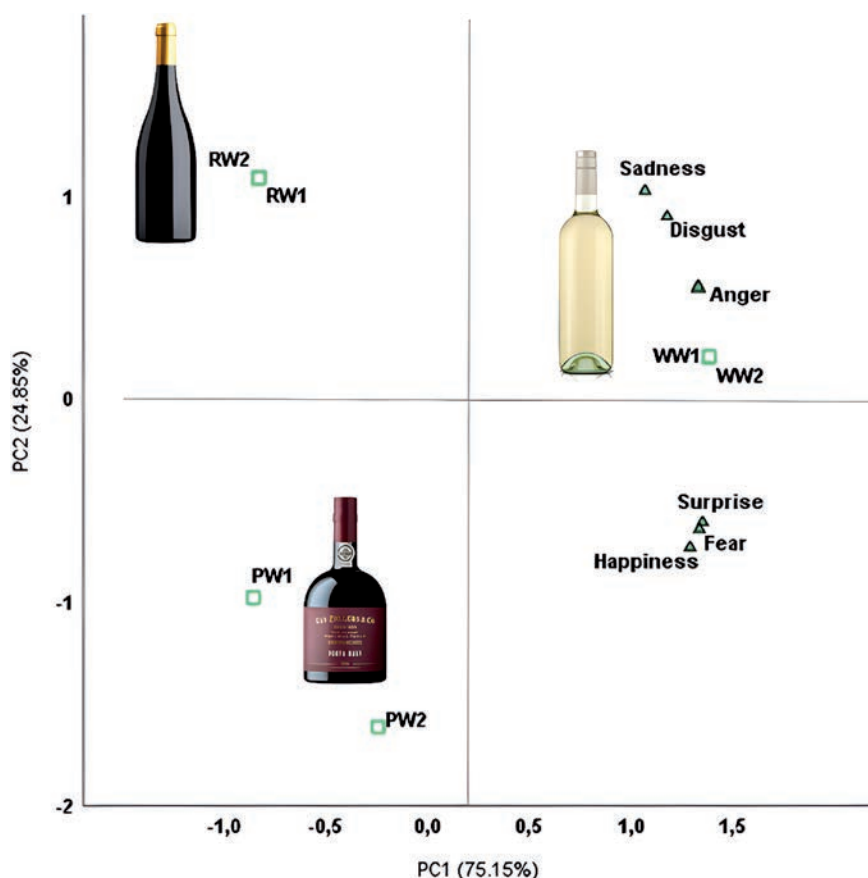


Figure 4.
 A detailed graphic produced following Principal Component Analysis (PCA) reveals that white, red, and Port wines from the Douro region are categorized based on the emotions they evoke (adapted from Marques and Vilela [15]). RW (red wine), WW (white wine), and PW (Port wine).

holistic assessment of emotional engagement in food and wine research. It highlights how digital emotion recognition tools can deepen insights into consumer preferences, support innovation, and elevate experiential marketing strategies.

4.2 Case studies of emo-sensory profiling in food matrices

While most of the early emo-sensory profiling research has concentrated on wine and other beverages, recent studies have demonstrated the applicability of these methodologies to solid and semi-solid food matrices. This extension reflects the growing interest in understanding how affective responses interact with multisensory food attributes to shape consumer perception, preference, and decision-making. Among the most studied categories are chocolate, yogurt, and condiments, owing to their complex sensory profiles.

Chocolate has been extensively profiled using both explicit tools (e.g., the EmoSensory® wheel) and implicit techniques (e.g., facial expression analysis). In their development of the EmoSensory® wheel, Schouteten et al. [28] applied the method to various food products, including chocolate, cola, and crisps. Their findings

showed that milk chocolate was linked to comforting emotions, such as “happy” and “relaxed,” while dark chocolate evoked more complex responses, including “sophisticated” or “bitter.” These emotional patterns were consistent with the products’ flavor profiles. They demonstrated the tool’s capacity to capture emotion-sensory interactions across different food categories, underscoring chocolate’s potential as a vehicle for emotion-driven marketing and innovation.

Similarly, Brückner et al. [22] investigated the role of emotional attributes in yogurt preference through a conjoint analysis combining hedonic ratings with an emotional lexicon. Their results revealed that descriptors such as “refreshing,” “natural,” and “soothing” had a significant impact on consumer choice, often exceeding the influence of price or nutritional content. This highlights the relevance of affective factors in post-consumption evaluation and pre-consumption expectation formation, with implications for product design and targeted marketing.

Extending this work to basic condiments, de Wijk et al. [39] examined emotional responses to soy sauce using a combination of facial expression analysis and remote photoplethysmography (rPPG). Their study demonstrated that product familiarity and branding modulated both emotional valence and physiological indicators, supporting the role of cognitive-affective integration in food perception, even for simple products.

Collectively, these studies demonstrate the methodological versatility and practical relevance of emo-sensory profiling in the food domain. The integration of affective science with sensory evaluation enables a more comprehensive understanding of consumer behavior.

5. Challenges and limitations

Despite the growing interest and application of emo-sensory profiling in sensory and consumer contexts, its implementation faces several methodological, technological, and interpretative challenges and limitations.

One of the primary challenges is the subjectivity of emotional responses, which can be influenced by various factors, including cultural, individual, contextual, and even physiological factors [41, 42]. The same food or beverage sample may trigger distinct emotions in consumers from different cultural backgrounds or emotional states, making it difficult to standardize protocols and ensure comparability between studies. Furthermore, emotional verbal or pictorial scales require careful linguistic and cultural validation, especially in multilingual or multicultural contexts [43].

Another challenge is integrating emotional reading technologies, such as facial recognition software (e.g., FaceReader) or physiological sensors. Although these tools enable detailed tracking of emotional responses, their application in real-world or dynamic environments, such as tastings at open-air events, fairs, or wine tourism experiences, remains limited by logistical, ethical, and privacy constraints [40]. Calibration of these technologies also requires controlled environments and specialized technical training, which limits their applicability for small businesses or artisanal producers [15].

From a statistical perspective, the analysis of emotional responses in food studies benefits from robust multivariate and machine learning approaches, as demonstrated by Álvarez-Pato et al. [35], who successfully combined facial emotion recognition, galvanic skin response, and heart rate data to predict consumer acceptance. Nonetheless, applying such complex techniques, ranging from data fusion methods

to advanced predictive modeling, can pose significant barriers to adoption outside academic or specialized research settings. The lack of benchmarks and public data-bases for training and validating models limits the comparability and reproducibility of results.

Additionally, establishing direct links between emotional responses and consumer behavior remains a significant challenge. Although emotional profiling captures affective reactions, translating these into real-world decisions is mediated by multiple variables such as price, availability, context, and prior habits. Ha and Lim [44] noted that emotional eating and food decisions are shaped by complex interplays among emotional states, eating styles, individual differences, and food types, making it challenging to generalize the emotional effects on consumption behavior. These findings highlight that while emotions can influence food-related choices, their predictive power is limited by individual and contextual variability.

Finally, it is essential to emphasize that the sustainable and ethical development of emotional profiling relies on critical reflection on how emotional data are collected, processed, and interpreted. Beyond ensuring consumer privacy and transparency in research goals, addressing issues such as informed consent, algorithmic bias, and the potential for emotional manipulation is essential. As noted by Gremsl and Hödl [45], the legal and ethical challenges of emotional AI demand robust safeguards, especially in contexts involving vulnerable consumers. Similarly, Latif et al. [46] emphasize that deploying AI-based emotion recognition systems without clear ethical guidelines risks undermining public trust and exacerbating inequalities in consumer interactions.

Despite these challenges, research continues to evolve, seeking integrated and accessible solutions that combine scientific rigor with practical applicability, particularly through low-cost digital platforms, specialized training, and more explainable predictive models.

6. Emerging trends and innovation: Implications for the agri-food and wine industries

Emo-sensory profiling is rapidly transforming the agri-food and wine industries, propelled by technological advances, evolving consumer preferences, and the integration of emotional intelligence into product development and marketing strategies. The fusion of Artificial Intelligence (AI) with sensory technologies enables processing large and complex datasets, allowing real-time analysis of emotional and sensory responses. Machine learning algorithms can identify subtle patterns in how consumers react to specific aromas, tastes, and textures, providing valuable insights that inform the design of products tailored to evoke targeted emotional responses. This level of personalization fosters deeper emotional connections between consumers and brands, enhancing loyalty and satisfaction. In the wine industry, non-invasive tools such as the electronic nose (E-nose), often integrated with artificial intelligence (AI), are increasingly used to assess aroma profiles, detect defects, and optimize production processes. These innovations are not only cost-effective but also accelerate decision-making and enhance consistency in quality, enabling winemakers to respond swiftly to market demands and sensory trends [47].

A growing segment of consumers is increasingly drawn to wines that reflect authenticity, health consciousness, and environmental responsibility. This evolving preference has fueled the popularity of organic, biodynamic, and low-intervention

wines, which are perceived as more natural and less manipulated. Moreover, there is a rising demand for products with lower alcohol content and minimal use of chemical additives, aligning with health-oriented lifestyles and ethical consumption trends. Producers are responding by embracing transparency, reducing technological interventions, and emphasizing the narrative surrounding indigenous grape varieties and the cultural identity of wine regions. These elements reinforce consumer trust and enhance emotional engagement through distinctive and memorable sensory experiences [48, 49]. Moreover, sustainability has emerged as a key driver of innovation in the agri-food and wine industries. Producers are increasingly adopting regenerative agriculture, renewable energy sources, and eco-friendly packaging to reduce environmental impact and align with the values of eco-conscious consumers. These measures contribute to improved environmental performance and serve as strategic tools to enhance brand reputation and consumer trust. In regions such as Europe and Latin America, where climate change is mounting pressure on traditional production models, initiatives aimed at achieving carbon neutrality and reducing water consumption are gaining significant traction. Such practices are often guided by life cycle assessment approaches that help identify critical areas for improvement and foster more sustainable production systems [50].

The emotional dimension of sensory perception is increasingly central to product innovation and branding. By capturing and analyzing emotional responses through facial recognition, biometric feedback, and verbal expression, producers can better understand the affective impact of their products. This understanding informs product formulation and marketing narratives that connect with consumers on a deeper level. Emotional branding, immersive storytelling, and aligning brand identity with consumer aspirations contribute to stronger emotional engagement and differentiation in saturated markets. As such, emo-sensory profiling is becoming a strategic tool for product and experience design. At the same time, the expansion of these technologies raises important ethical considerations. Data privacy, informed consent, and algorithmic transparency must be addressed to ensure consumer trust and responsible innovation. Regulatory frameworks and standardized methodologies are needed to safeguard users and establish credibility in the field [51].

Looking ahead, the convergence of AI, emo-sensory analytics, and sustainability trends presents an unprecedented opportunity for the agri-food and wine industries to reinvent how they develop, market, and deliver products. By leveraging these innovations, producers can create meaningful and multisensory experiences that meet the evolving needs of a diverse and emotionally engaged consumer base.

7. Conclusion

Sensory attributes, label cues, and information, such as organic or provenance claims, significantly shape consumer expectations, opinions, and overall pleasantness in food and wine experiences. Direct and indirect measures of liking, as well as consumer segmentation, provide a nuanced understanding of preferences. Aligning sensory qualities and marketing cues with consumer expectations can enhance satisfaction and drive positive dining experiences.

This review emphasizes the importance of integrating sensory science with consumer psychology and marketing strategies to accurately predict and meet consumer demands. Moreover, novel methodologies such as emotional profiling, eye tracking, and implicit associations offer valuable insights into the unconscious drivers

of choice, complementing traditional hedonic assessments. Future research should investigate how multisensory integration, contextual factors (e.g., the consumption environment), and cultural dimensions impact perception and acceptance.

Ultimately, a holistic approach that combines product optimization with tailored communication strategies can support the development of more appealing, sustainable, and health-promoting food and wine products, thereby contributing to consumer enjoyment and informed, responsible consumption behaviors.

Conflict of interest

The authors declare that they have no conflict of interest.

Author details

Catarina Marques and Alice Vilela*
CQ-VR, Chemistry Research Center, Department of Agronomy, School of Agrarian and Veterinary Sciences, University of Trás-os-Montes and Alto Douro, Portugal

*Address all correspondence to: avimoura@utad.pt

IntechOpen

© 2025 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. 

References

- [1] Zhu Y, Su Q, Jiao J, Kelanne N, Kortessniemi M, Xu X, et al. Exploring the sensory properties and preferences of fruit wines based on an online survey and partial projective mapping. *Food*. 2023;**12**(9):1844. DOI: 10.3390/foods12091844
- [2] Lattey K, Bramley B, Francis I. Consumer acceptability, sensory properties and expert quality judgements of Australian cabernet sauvignon and shiraz wines. *Australian Journal of Grape and Wine Research*. 2010;**16**:189-202. DOI: 10.1111/J.1755-0238.2009.00069.X
- [3] Kustos M, Heymann H, Jeffery D, Goodman S, Bastian S. Intertwined: What makes food and wine pairings appropriate? *Food Research International*. 2020;**136**:109463. DOI: 10.1016/j.foodres.2020.109463
- [4] Kustos M, Goodman S, Jeffery D, Bastian S. Appropriate food and wine pairings and wine provenance information: Potential tools for developing memorable dining experiences. *Food Quality and Preference*. 2021;**94**:104297. DOI: 10.1016/J.FOODQUAL.2021.104297
- [5] Lick E, König B, Kpessa M, Buller V. Sensory expectations generated by colours of red wine labels. *Journal of Retailing and Consumer Services*. 2017;**37**:146-158. DOI: 10.1016/J.JRETCONSER.2016.07.005
- [6] Jürkenbeck K, Spiller A. Importance of sensory quality signals in consumers' food choice. *Food Quality and Preference*. 2021;**90**:104155. DOI: 10.1016/j.foodqual.2020.104155
- [7] Apaolaza V, Hartmann P, Echebarria C, Barrutia J. Organic label's halo effect on sensory and hedonic experience of wine: A pilot study. *Journal of Sensory Studies*. 2017;**32**:e12243. DOI: 10.1111/JOSS.12243
- [8] Visalli M, Mahieu B, Dubois M, Schlich P. Hedonic valence of descriptive sensory terms as an indirect measure of liking: A preliminary study with red wines. *Food Quality and Preference*. 2023;**108**:104861. DOI: 10.1016/j.foodqual.2023.104861
- [9] Souza-Coutinho M, Brasil R, Souza C, Sousa P, Malfeito-Ferreira M. Consumers associate high-quality (fine) wines with complexity, persistence, and unpleasant emotional responses. *Food*. 2020;**9**(4):45. DOI: 10.3390/foods9040452
- [10] Francis I, Williamson P. Application of consumer sensory science in wine research. *Australian Journal of Grape and Wine Research*. 2015;**21**:554-567. DOI: 10.1111/AJGW.12169
- [11] Ruiz-Capillas C, Herrero AM. Sensory analysis and consumer research in new product development. *Food*. 2021;**10**(3):582. DOI: 10.3390/foods10030582
- [12] Herz RS, Eliassen JC, Beland SL, Souza T. Neuroimaging evidence for the emotional potency of odor-evoked memory. *Neuropsychologia*. 2004;**42**(3):371-378. DOI: 10.1016/j.neuropsychologia.2003.08.009
- [13] Masaoka Y, Sugiyama H, Yoshida M, Yoshikawa A, Honma M, Koiwa N, et al. Odors associated with autobiographical memory induce visual imagination of emotional scenes as well as orbitofrontal-fusiform activation. *Frontiers in Neuroscience*. 2021;**15**:709050. DOI: 10.3389/fnins.2021.709050

- [14] Qasim SE, Mohan UR, Stein JM, Jacobs J. Neuronal activity in the human amygdala and hippocampus enhances emotional memory encoding. *Nature Human Behaviour*. 2023;7(5):754-764. DOI: 10.1038/s41562-022-01502-8
- [15] Marques C, Vilela A. FaceReader insights into the emotional response of Douro wines. *Applied Sciences*. 2024;14(21):10053. DOI: 10.3390/app142110053
- [16] Dantec M, Mantel M, Lafraire J, Rouby C, Bensafi M. On the contribution of the senses to food emotional experience. *Food Quality and Preference*. 2021;92:104120. DOI: 10.1016/j.foodqual.2020.104120
- [17] Mastinu M, Melis M, Yousaf NY, Barbarossa IT, Tepper BJ. Emotional responses to taste and smell stimuli: Self-reports, physiological measures, and a potential role for individual and genetic factors. *Journal of Food Science*. 2023;88(S1):65-90. DOI: 10.1111/1750-3841.16300
- [18] Campo R, Rosato P, Battisti E. Multisensory analysis and wine marketing: Systematic review and perspectives. *British Food Journal*. 2022;124(10):3274-3292. DOI: 10.1108/BFJ-03-2021-0222
- [19] Yuan W, Guo F, Li M, Song H. Effects of sensory cues on consumers' wine taste perceptions and behavior: Evidence from a wine-tasting experiment. *International Journal of Contemporary Hospitality Management*. 2024;36(12):4171-4191. DOI: 10.1108/IJCHM-08-2023-1160
- [20] Cosme F, Rocha T, Marques C, Barroso J, Vilela A. Innovative approaches in sensory food science: From digital tools to virtual reality. *Applied Sciences*. 2025;15:4538. DOI: 10.3390/app15084538
- [21] Marques C, Mota J, Aires A, Dinis L-T, Vilela A, Correia E. Unveiling port wine vinegar: A comprehensive study on chemical and sensory profile. *International Journal of Gastronomy and Food Science*. 2025;40:101160. DOI: 10.1016/j.ijgfs.2025.101160
- [22] Brückner K, Emberger-Klein A, Menrad K. The role of emotions in food-related decision-making: A choice-based conjoint analysis of yogurt preferences. *Journal of Food Products Marketing*. 2023;29(6):177-196. DOI: 10.1080/10454446.2023.2227575
- [23] Elali I, M'Bailara K, Sanders V, Riquier L, de Revel G, Tempère S. Is wine an emotional object? Measurements of the subjective and automatic components of emotions in a wine-tasting situation. *OENO one*. 2022;22(5):954-970. DOI: 10.1037/emo0000894
- [24] Pérez MQ, Martínez Beltrán ET, López Bernal S, Horna Prat E, Montesano Del Campo L, Fernández Maimó L, et al. Data fusion in neuromarketing: Multimodal analysis of biosignals, lifecycle stages, current advances, datasets, trends, and challenges. *Information Fusion*. 2024;105:102231. DOI: 10.1016/j.inffus.2024.102231
- [25] da Silva FN, Minim LA, Filho TL, da Silva Xavier Costa AA, Vidigal MCTR, Minim VPR. Immersive virtual contexts, engagement, and emotions: How do these factors influence sensory acceptance? *Food Research International*. 2025;207:116106. DOI: 10.1016/j.foodres.2025.116106
- [26] Marques C, Correia E, Dinis L-T, Vilela A. An overview of sensory characterization techniques: From classical descriptive analysis to the emergence of novel profiling methods. *Food*. 2022;11(3):255. DOI: 10.3390/foods11030255

- [27] Kaneko D, Toet A, Brouwer AM, Kallen V, van Erp JBF. Methods for evaluating emotions evoked by food experiences: A literature review. *Frontiers in Psychology*. 2018;**9**:911. DOI: 10.3389/fpsyg.2018.00911
- [28] Schouteten JJ, De Steur H, Gellynck X. The EmoSensory® wheel. In: Meiselman HL, editor. *Emotion Measurement*. 2nd ed. Cambridge: Woodhead Publishing; 2021. pp. 471-492. DOI: 10.1016/B978-0-12-
- [29] Kaneko D, Toet A, Ushiana S, Brouwer AM, Kallen V, van Erp JB. EmojiGrid: A 2D pictorial scale for cross-cultural emotion assessment of negatively and positively valenced food. *Food Research International*. 2019;**115**:541-551. DOI: 10.1016/j.foodres.2018.09.049
- [30] Küster D. The face behind the mask: Thermography of the face. In: *Body Language Communication*. 1st ed. Cham: Palgrave Macmillan; 2025. pp. 285-313. DOI: 10.1007/978-3-031-70064-4_12
- [31] Marques C, Dinis L-T, Modesti M, Bellincontro A, Correia E, Vilela A. Exploring the influence of terroir on Douro white and red wines characteristics: A study of human perception and electronic analysis. *European Food Research and Technology*. 2024;**250**:3011-3027. DOI: 10.1007/s00217-024-04607-8
- [32] Levrini GRD, Jeffman dos Santos M. The influence of Price on purchase intentions: Comparative study between cognitive, sensory, and neurophysiological experiments. *Behavioral Sciences*. 2021;**11**(2):16. DOI: 10.3390/bs11020016
- [33] Wang QJ, Barbosa Escobar F, Alves Da Mota P, Velasco C. Getting started with virtual reality for sensory and consumer science: Current practices and future perspectives. *Food Research International*. 2021;**145**:110410. DOI: 10.1016/j.foodres.2021.110410
- [34] Torrico DD, Han Y, Sharma C, Fuentes S, Gonzalez Viejo C, Dunshea FR. Effects of context and virtual reality environments on the wine-tasting experience. *Acceptability, and Emotional Responses of Consumers Foods*. 2020;**9**(2):191. DOI: 10.3390/foods9020191
- [35] Álvarez-Pato VM, Sánchez CN, Domínguez-Soberanes J, Méndez-Pérez DE, Velázquez R. A multisensor data fusion approach for predicting consumer acceptance of food products. *Food*. 2020;**9**(6):774. DOI: 10.3390/foods9060774
- [36] Yang J, Lee J. Consumer perception of red wine by the degree of familiarity using consumer-based methodology. *Food*. 2021;**10**:749. DOI: 10.3390/foods10040749
- [37] Loijens L, Krips O. FaceReader Methodology Note. Noldus Information Technology. Available from: <https://info.noldus.com/free-white-paper-on-facereader-methodology>; [Accessed: March 2025]
- [38] ISO 3591. *Sensory Analysis—Apparatus—Wine-Tasting Glass*. Geneva, Switzerland: ISO; 1977. Available from: <https://www.iso.org/standard/9002.html> [Accessed: September 10, 2024]
- [39] Wijk RA, Ushiana S, Ummels M, Zimmerman P, Kaneko D, Vingerhoeds MH. Reading food experiences from the face: Effects of familiarity and branding of soy sauce on facial expressions and video-based RPPG heart rate. *Food*. 2021;**10**(6):1345. DOI: 10.3390/foods10061345

- [40] Almeida D, Shmarko K, Lomas E. The ethics of facial recognition technologies, surveillance, and accountability in an age of artificial intelligence: A comparative analysis of US, EU, and UK regulatory frameworks. *AI and Ethics*. 2022;**2**(3):377-387. DOI: 10.1007/s43681-021-00077-w
- [41] Huang X, Lajoie SP. Social emotional interaction in collaborative learning: Why it matters and how can we measure it? *Social Sciences and Humanities Open*. 2023;**7**(1):100447. DOI: 10.1016/j.ssaho.2023.100447
- [42] Lim N. Cultural differences in emotion: Differences in emotional arousal level between the east and the west. *Integrative Medicine Research*. 2016;**5**(2):105-109. DOI: 10.1016/j.imr.2016.03.004
- [43] Wang P, Ganushchak L, Welie C, van Steensel R. The dynamic nature of emotions in language learning context: Theory, method, and analysis. *Educational Psychology Review*. 2024;**36**(4):105. DOI: 10.1007/s10648-024-09946-2
- [44] Ha OR, Lim SL. The role of emotion in eating behavior and decisions. *Frontiers in Psychology*. 2023;**14**:1265074. DOI: 10.3389/fpsyg.2023.1265074
- [45] Gremsl T, Hödl E. Emotional AI: Legal and ethical challenges. *Information Polity*. 2022;**27**:1-12. DOI: 10.3233/IP-211529
- [46] Latif S, Ali HS, Usama M, Rana R, Schuller B, Qadir J. AI-based emotion recognition: Promise, peril, and prescriptions for prosocial path. *arXiv preprint arXiv:2211.07290*. 2022;**1**:1-13. Disponível em: <https://arxiv.org/abs/2211.07290>
- [47] Alfieri G, Modesti M, Riggi R, Bellincontro A. Recent advances and future perspectives in the E-nose technologies addressed to the wine industry. *Sensors*. 2024;**24**(7):2293. DOI: 10.3390/s24072293
- [48] Moscovici D, Gow J, Alonso Ugaglia A, Rezwanul R, Valenzuela L, Mihailescu R. Consumer preferences for organic wine—Global analysis of people and place. *Journal of Cleaner Production*. 2022;**368**:133215. DOI: 10.1016/j.jclepro.2022.133215
- [49] Pickering GJ, Best M. An exploration of consumer perceptions of sustainable wine. *Journal of Wine Research*. 2023;**34**(3):232-246. DOI: 10.1080/09571264.2023.2254249
- [50] Guerra M, Ferreira F, Oliveira AA, Pinto T, Teixeira CA. Drivers of environmental sustainability in the wine industry: A life cycle assessment approach. *Sustainability*. 2024;**16**(13):5613. DOI: 10.3390/su16135613
- [51] Santos V, Ramos P, Almeida N, Santos-Pavón E. Consumer expectations and values: The role of digitalization in understanding and meeting consumer needs. *BIO Web of Conferences*. 2023;**68**:03012. Presented at: 44th World Congress of Vine and Wine; 2023; Cádiz, Spain. DOI: 10.1051/bioconf/20236803012

Consumers' Acceptability and Purchase Intent of Cow Blood Sausage in South African Ethnic Groups

Ennet Moholisa, Lizelle Rheeders, Kealeboga Mosimanyana and Phillip Strydom

Abstract

Among edible meat by-products, blood sausages are a well-known traditional meat by-product in many countries. They come under different names depending on the country of origin. Every country has its own recipe. Despite the widespread production and consumption of blood sausages in other parts of the world, this meat by-product is not well-known in South Africa. In this study, four versions of sausages were developed with varying quantities of cow blood mixed with pig skin, cooked pearled barley and beef offal. The four recipes of sausages contained 5%, 15% and 30% cow blood. The fourth treatment contained no blood (0% blood), and it was used as the control. The sausages were presented to South African ethnic groups to evaluate consumer acceptance and purchase intent. The blood inclusion level in the sausage did not affect the sensory scores of the panellists for all the attributes investigated. The differences observed for the overall acceptability of the sausages for different treatment groups were very small and insignificant. Blood sausages were generally accepted by consumers, with at least a 66% acceptability score. The results of the purchase intent showed that, regardless of the blood inclusion level in the sausage, there was a high probability that consumers would buy the blood sausages if they were available in the market.

Keywords: cow blood sausage, sensory analysis, consumer, ethnic group, purchase intent, food neophobia

1. Introduction

Blood sausages are known as ethnic foods in many countries of the world. They are ready-to-eat meat by-products of the slaughterhouse. Their main ingredients are blood and fat; however, other ingredients may be used depending on the sausage's country of origin. Blood sausages have diverse regional variations and cultural significance

worldwide. They are very popular in Europe, South America, and Asia. They are also found in some countries in North America [1]. In Africa, blood is known to be a traditional diet of the Masai (also spelled Maasai) people in Kenya and Tanzania. Masai's traditional blood sausage is called Mutura, often nicknamed African sausage [2].

Despite the widespread consumption of blood sausages in other parts of the world, this meat by-product is a lesser-known food product in South Africa. The blood sausages that are sold in the South African food market are found in niche butcher shops owned by immigrants [3]. However, there is evidence that whole blood has been used as a food product by some of the ethnic groups in South Africa [3–5]. These ethnic groups mix the blood with edible offal (intestines, tripe, tongue, spleen, etc.), and the cooked mixture is served with “pap” (a type of thick consistency porridge made from maize meal). Sometimes the blood and offal mixture is mixed with maize meal. The recipe for this food product is a non-standardised formulation subject to preparer variability. This food product is seldom made, since it is made only when the animal is slaughtered for traditional ceremonies [4]. It is eaten immediately after cooking.

Considering that South African abattoirs produce livestock blood in high quantities, and edible offal is relatively cheap and sold everywhere in South Africa and mostly sold fresh with no value added to it. The aim of this study was to optimise this existing food product made from livestock blood to develop cow blood sausages mixed with offal, barley and rusk to determine the consumer acceptability and purchase intent within the South African ethnic groups.

2. Materials and methods

2.1 Preparation of the sausage models

A total of 20 kg (5 kg/treatment x 4 products) of cooked blood sausages was produced in six replicates using cow blood, beef trimmings, cow offal (heart and kidney), pig skin, cooked pearled barley and rusk (**Table 1**). The production of blood sausages was done with some modifications according to the method described in Ref. [6]. Meat trimmings, heart, kidney and pig skin were first trimmed to remove excess fat and membranes. Four treatment groups were formulated to contain 0% (no blood), 5%, 15% and 30% blood (**Table 1**). Water was added to compensate for blood. The blood used for the development of sausages was collected from the cattle that are slaughtered at the experimental abattoir of the Agricultural Research Council-Animal Production, South Africa. The blood was collected using a hollow knife with a closed draining system until it reached the collecting vessel containing 0.4% tri-sodium citrate. The collected blood was immediately cooled to 3°C and stored at 0°C until it was used for manufacturing sausages the following day.

The blood was sieved to separate and remove suspended solids. Cooked pork skin was ground along with the meat, heart, kidney and fat using Berkel E-222 Meat Grinder (5 mm mincing plate). The blood, cereals (rusk, cooked barley), crispy fried onions and spices were mixed for one minute. The mixture was then left standing for 5 minutes to allow for hydration. After which it was added to the comminuted meat mixture and mixed. Natural hog casings, 50 mm in diameter (Gold Crown, Crown National) were filled with the mixture using Viking sausage filler. After filling, the blood sausages were fan grilled in the oven (Mielé, model H217) at 120°C until the temperature of the geometric centre reached 80°C. This was followed by cooling and storage of cooked sausages at 4°C for flavour development. The sausages were served at least three days after cooking.

Composition	¹ Product A	² Product B	³ Product C	⁴ Product D
Ingredient inclusion level				
	Kg	%	%	%
Raw blood/iced water	1.500			
Raw cow blood		0.00	5.00	15.00
Water		30.00	25.00	15.00
Heart	0.315	6.21	6.21	6.21
Kidney	0.185	3.65	3.65	3.65
Beef trimmings	0.500	9.85	9.85	9.85
pig skin	0.500	9.85	9.85	9.85
Pork backfat	1.000	19.70	19.70	19.70
Rusk	0.500	9.85	9.85	9.85
Cooked Pearl barley	0.250	4.93	4.93	4.93
Raw onion	0.125	2.46	2.46	2.46
*Seasoning	0.120	2.36	2.36	2.36
Salt	0.080	1.58	1.58	1.58
Total	5.075	100. 44	100. 44	100. 44

¹Sausages containing no blood (0%);
²Sausage containing 5% cow blood;
³Sausage containing 15% cow blood;
⁴Sausage containing 30% cow blood.
*Seasoning = consisted of parsley, garlic powder, black pepper, cumin, nutmeg and marjoram.

Table 1.
The formulation of four batches of sausages containing 0, 5, 15 and 30% of each of cow and pig blood.

2.2 Sensory analysis

The sensory analysis was carried out according to the guidelines of the American Meat Science Association (AMSA) [7] (described below) in the sensory analysis facility that conforms to the American Society for Testing and Materials (ASTM) (1996) design guidelines for sensory facilities.

2.2.1 Panel recruitment

The recruitment of consumers was a convenience sampling made by phone, e-mail or personal interview, referrals, and advertisements on social media or pamphlets. Consumers were recruited based on their interest and availability to participate in the study, and only those who reported an affinity for blood- and viscera-based products were allowed to participate. The familiarity of the cooked livestock blood-based food products was assessed and measured on a bipolar scale of yes or no. The consumers were asked whether they had previously eaten or tasted cooked livestock blood-based food products.

The major part of the sensory panel was recruited from the staff of the Agricultural Research-Animal Production (ARC-AP), Pretoria, South Africa. The other part of the panel was recruited outside the ARC-AP, through personal accessibility and proximity to

the researchers. The sensory evaluation was carried out with 86 consumer panel consisting of both males and females of ages ranging from 20 to 64 years, from different South African ethnic groups. Since blood sausage is a novel product to South Africans, the Food Neophobia Scale (FNS) developed in Ref. [8] was used to measure neophobic reactions of the participants towards the sausages. An adapted food neophobia questionnaire consisted of six statements designed to measure various dimensions of food-related fear and aversion, with responses on three-point scale ranging from 1 to 3 (1 = yes, 2 = No, 3 = Sometimes) was administered to consumers.

2.2.2 Sample preparation and tasting

The chilled sausages were cut into 1 cm thick slices and wrapped with aluminium foil. The samples were then reheated in the convection oven and kept warm (50°C) until served to the panellists. Special care was taken not to allow the samples to dry out or cook any further. The samples were coded with randomised, three-digit codes unique to each sample, representing one of the four treatment groups. The four samples per treatment group were tasted in duplicate. To avoid the halo effect, the tasting of the samples was done in two sessions. At each session each respondent received a slice of 1 cm piece of the sausage sample per treatment from four treatment groups. When serving the samples were rotated to prevent bias. The sensory evaluation was performed in individual booths of the sensory laboratory at ambient temperature. The booths were fitted with overhead light fittings with red-coloured bulbs emitting only red light to mask any possible colour variations between different samples. Each respondent received a four-page questionnaire consisting of a five-point hedonic score per page ranging from 1 = dislike extremely to 5 = like extremely. The respondents were then expected to score each sample individually for the following attributes: aroma, flavour, texture, juiciness and overall acceptability. Tap water and sliced carrots were presented at room temperature as a palate cleansers between the samples.

2.2.3 Purchase intent

The purchasing intent was evaluated using the bipolar scale of yes or no [3].

2.2.4 Statistical analysis

The consumer panel data were subjected to ANOVA using the general linear models procedure (PROC GLM) in statistical analysis system (SAS) version 9.4 statistical software [9]. The ANOVAs were performed on the original scores to do Friedman's nonparametric analysis of variance [10]. Fisher's protected t-Least Significant Differences (LSDs) were calculated ($\alpha = 0.05$) to compare means of significant effects on the original scores [11]. Furthermore, tabulated frequencies were tested for association (patterns) using a Chi-Square (χ^2) test [10]. These tests were performed with SAS version 9.4 statistical software [8].

3. Results and discussions

A breakdown of the 86-member consumer panel is shown in **Table 2**, and the percentage frequency distribution of consumers' previous consumption of the cooked

Demographic categories	Percentage number of panellists
Age groups	
20–29	13
30–39	21
40–49	26
50–59	33
>60	7
Gender	
Female	42
Male	58
Ethnic groups	
1. Sotho	48
2. Venda	8
3. Tsonga	13
4. Nguni	23
5. Other	8
<i>Ethnic groups = 1. Sotho (Sotho, Tswana, Pedi), 2. Venda, 3. Tsonga, 4. Nguni (Zulu, Xhosa, Ndebele, Swati), 5. Other (whites and coloureds).</i>	

Table 2.
Demographic description of the consumer panel.

livestock blood food products is shown in **Table 3**. The familiarity of the cooked livestock blood-based food products significantly increased with the increase in age (50–60 years) of the panellists. This could be expected because these food products are regarded as ethnic foods, and the majority of younger people might not be familiar with their taste. Although not significant, panellists who had tasted cooked livestock blood before were more than panellists who had not tasted these food products in all ethnic groups.

Descriptive sensory results of the cow blood sausages are shown in **Table 4**. The blood inclusion level in the sausage did not affect sensory scores of the panellists for all the attributes. The variation (s.d.) in consumer responses was a bit higher, indicating a large difference in the liking of the attributes. The probable reason could be the use of untrained panels. It has been shown that untrained panellists are not able to detect more subtle differences in food products, unlike trained panellists who are inherently more sensitive to organoleptic traits. However, it is generally accepted that untrained consumers are capable of evaluating the sensory characteristics of food products [12], and the results obtained from consumer panels can closely reflect the general public's acceptance of a food product [13]. All the sausages from different treatment groups were generally liked by the consumers (**Table 4**). The differences observed for the overall acceptability of the sausages for different treatment groups were very small and insignificant. On the hedonic scale ranging from 1 (dislike very much) to 5 (like very much), the highest score for all the sausages from different treatment groups was four (4 = like).

The sensory fingerprint in **Figure 1** was used to depict or simplify the descriptive sensory scores in **Table 4**. The sensory fingerprint reiterates **Table 4** by clearly

Categories	*Yes	*No	χ^2 (df)	P-value
Age groups				
20–29	45.45	54.55	21.12 (4)	0.0003
30–39	47.06	52.94		
40–49	33.33	66.67		
50–59	92.67	7.14		
>60	66.64	33.33		
Ethnic groups				
1. Sotho	56.41	43.59		NS
2. Venda	50.00	50.00		
3. Tsonga	63.64	36.36		
4. Nguni	70.00	30.00		
5. Other	57.14	42.86		
Ethnic groups = 1. Sotho (Sotho, Tswana, Pedi), 2. Venda, 3. Tsonga, 4. Nguni (Zulu, Xhosa, Ndebele, Swati), 5. Other (Whites and coloureds).				
NS=Not significant.				
df = degrees of freedom. *Yes = panellists who had previously tasted cooked livestock blood-based food products.				
No = panellists who had not tasted cooked livestock blood-based food products.				

Table 3.
Frequency distribution (%) of consumers' previous consumption of the cooked livestock blood food products.

Blood inclusion level	Attributes				
	Aroma	Flavour	Juiciness	Texture	Overall acceptability
0%	3.7 ± 1.09	3.7 ± 1.07	3.8 ± 1.04	3.7 ± 1.05	3.8 ± 1.07
5%	3.7 ± 1.12	3.6 ± 1.19	3.7 ± 1.07	3.6 ± 1.13	3.7 ± 1.16
15%	3.7 ± 1.10	3.7 ± 1.16	3.6 ± 1.15	3.6 ± 1.15	3.7 ± 1.17
30%	3.6 ± 1.08	3.7 ± 1.01	3.6 ± 1.07	3.6 ± 0.99	3.8 ± 1.09
P-value	0.3358	0.5873	0.1715	0.8100	0.4115

Hedonic scale; 1 = dislike very much, 2 = dislike, 3 = like nor dislike, 4 = like, 5 = like very much.

Table 4.
Descriptive sensory analysis of cow blood sausages formulated with 0, 5, 15 and 30% blood (Means ± s.d.).

displaying the magnitude of variation in attributes of the different sausage treatments with the mean values of sensory scores. Sausages containing no blood were scored slightly higher for aroma, texture, juiciness and overall acceptability than all other sausages of different treatment groups. Juiciness decreased with the increase in the amount of blood used in the preparation of the sausage. Sausages containing the highest amount of blood (30%) received the lowest score for juiciness. This was reflected by the texture of the sausages. All sausages formulated with blood had the lowest score for texture. Interestingly, sausages containing 30% blood were scored

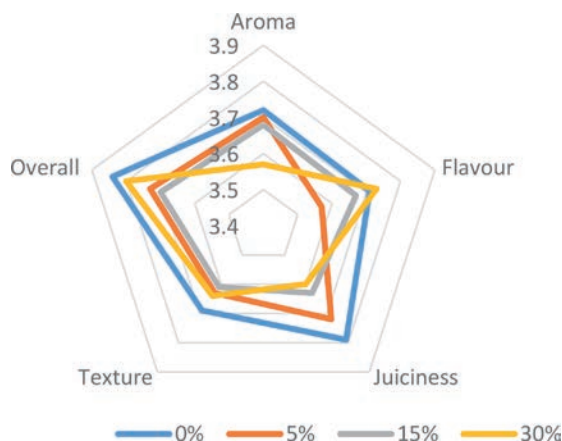


Figure 1.
 Graphical presentation by means of a spider plot for descriptive sensory properties of sausages formulated with 0, 5, 15 and 30% cow blood.

slightly higher for flavour and lowest for aroma compared to all other sausage treatments. It could be assumed that other sausages might have a bland taste compared to the liver taste of the 30% blood sausages; however, it is also obvious that the consumers did not like the liver aroma of the high blood content sausages. Besides individual preferences, many aromatic chemicals have lower detection thresholds than flavour compounds. This means that a smaller amount of a volatile compound can be perceived as an aroma than as a taste. If meat has a slightly livery taste, it may be due to a concentration of these compounds that is below the threshold for a strong aroma, but still above the threshold for taste [14, 15].

To estimate the degree of variation, frequencies were tested for association (patterns) on overall acceptability (**Table 5**). All the sausages were equally liked/accepted ($\chi^2 = 9.1$, 12 degrees of freedom (df); $P = 0.6887$) and the highest frequency was four (4 = like) and mirrored the results in **Table 4**. The second highest frequency score was five (5 = like very much). Sausages containing no blood had the highest (71%) frequencies for overall acceptability scores, while 30% and 15% blood sausages were scored higher (66%) than 5% blood sausages (61%). Dislike very much = (1) increased with the increase in age of the consumers. This shows that the sausages were more liked by younger panellists than older panellists. The plausible explanation could be that the younger panellists were more adventurous in tasting this novel product. Young adults are more open to trying novel products, while older people (>55 years of age) have high levels of food neophobia (reluctance to eat and/or avoidance of novel foods [16]). There were high frequencies ($\chi^2 = 21.24$, 16 df; $P = 0.0005$) for consumer panellists in all ethnic groups who liked the sausages compared to those who were neutral or did not like the sausages. The ethnic group 1 (Sotho, Pedi and Tswana) (70%) and the Tsonga group (68%) liked the sausages more than the other three ethnic groups. Since food preferences and acceptance are known to be associated with food exposure [16, 17], it could be expected that the Nguni group would like the sausages more than other groups because most of them were more familiar with the cooked livestock blood-based food products than the other groups (**Table 3**). However, it was not the case in the current study.

Hedonic scale							
Categories	1	2	3	4	5	χ^2 (df)	P-Value
Blood inclusion level in the sausage							
0%	3.47	9.83	15.61	41.04	30.06		
5%	3.43	17.14	12.57	31.14	29.71		NS
15%	5.85	11.7	16.96	37.43	28.07		
30%	2.96	12.43	18.93	36.69	28.99		
Age group							
20–29	0.00	14.77	13.64	43.18	28.41		
30–39	1.39	15.97	11.81	38.89	31.94		
40–49	6.82	14.20	17.05	39.20	22.73		NS
50–59	4.31	10.78	18.53	33.19	33.19		
>60	6.25	4.17	16.67	45.83	27.08		
Ethnic groups							
1. Sotho	5.18	12.50	12.20	34.45	35.67		
2. Venda	1.79	16.07	17.86	33.93	30.36		
3. Tsonga	4.55	13.64	13.64	31.82	36.36	41.24 (16)	0.0005
4. Nguni	1.88	11.88	20.63	46.88	18.75		
5. Other	3.57	12.50	12.79	48.21	8.93		
<i>Hedonic scale: 1 = dislike very much, 2 = dislike, 3 = Neither like nor dislike, 4 = like, 5 = Like very much. Ethnic groups = 1. Sotho (Sotho, Tswana, Pedi), 2. Venda, 3. Tsonga, 4. Nguni (Zulu, Xhosa, Ndebele, Swati), 5. Other (Whites and coloureds). NS=Not significant. df = degrees of freedom.</i>							

Table 5.

Frequency distribution of consumers (%) overall acceptability of the sausages formulated with 0, 5, 15 and 30% cow blood.

As previously presented by Moholisa et al. [3], the frequency distribution of consumers' purchase intent measured on the bipolar scale of yes or no is presented in **Table 6**. Regardless of the blood inclusion level in the sausages, the likelihood that consumers would purchase the blood sausages was very high. On average, consumers between the ages of 20 and 59 in all the ethnic groups who showed interest in purchasing the sausages were more than consumers (57 vs. 43%), panellists who would not purchase the products, with slight differences between treatment groups. A Higher percentage of elderly people (60–64 years old) showed less interest in purchasing the sausages. This was not surprising since the dislike very much (score = 1) increased with the increase in the age of the panel-lists (**Table 4**).

The summary of food neophobic responses of the consumers is shown in **Table 7**. The majority of the consumers responded yes to all food neophobic statements, showing that the participants in this study are not averse to ethnic or indigenous foods, and they can be described as neophilic consumers; those who tend to accept unfamiliar foods [18]. The positive responses were significant compared to the negative responses. This explains the higher acceptability and purchase intent of the blood sausages observed in **Tables 5** and **6**, respectively.

Categories	Purchase intent			
	Yes	No	χ^2 (df)	P-value
Blood inclusion level in the sausage				
0%	58.54	41.46		
5%	58.08	41.92	0.57(3)	NS
15%	54.82	45.18		
30%	56.60	43.40		
Age groups				
20–29	51.19	48.81		
30–39	64.66	35.34		
40–49	55.97	44.03	7.98 (4)	NS
50–59	58.19	41.81		
>60	43.75	56.25		
Ethnic groups				
1. Sotho	56.15	43.85		
2. Venda	64.29	35.05		
3. Tsonga	57.95	42.05	2.20 (4)	NS
4. Nguni	57.69	42.31		
5. Other	50.91	49.09		

Ethnic groups = 1. Sotho (Sotho, Tswana, Pedi), 2. Venda, 3. Tsonga, 4. Nguni (Zulu, Xhosa, Ndebele, Swati), 5. Other (White and coloureds). NS=Not significant.

Table 6.
Frequency distribution of consumers (%) purchase intent of the cow blood sausages formulated with 0, 5, 15 and 30% blood.

FNS/Statements	1 = Y	2 = N	3 = S	χ^2 (df)	P-value
I constantly taste new and different foods	35	9	29	15.23(2)	0.0005
I do not trust food if I do not know its ingredients/ contents	26	31	19	2.87 (2)	0.2383
I like ethnic/indigenous foods	60	8	7	73.52(2)	<.0001
If I go to a function or meetings or parties, I will eat new foods	49	11	15	34.88(2)	<.0001
I am afraid to eat food that I have never eaten before	29	38	9	17.39(2)	0.0002
I prefer healthy food/I only eat food that is appealing and tastes good	61	8	7	75.34(2)	<.0001

Scale 1–3; 1 = Y denotes, yes; 2 = N denotes, No; 3 = S denotes, Sometimes.

Table 7.
Frequency distribution of consumers' neophobic responses (%) towards the cow blood sausages.

4. Conclusions

The results of this study showed that although the blood sausages could be distasteful to some consumers, they could also be acceptable to others. The acceptability of the cow blood sausages formulated with cow offal and cereals had a consumer acceptability of 66% on average. A higher percentage of responses to food neophobic questions shows that the participants in this study are less averse to novel foods. This demonstrates that blood sausages might be acceptable to South African consumers. The high frequency distribution of consumers' purchase intent gives a clear indication that there is a high probability of these sausages being marketable if they are available in the South African food market. Despite these findings, care should be taken when interpreting the results of this study, since the study was carried out in one location. Future studies must explore longitudinal changes in consumer attitudes and rural-urban differences.

Acknowledgements

The National Research Foundation (Grant no: 134981) and Red Meat Research and Development, South Africa, provided financial support towards this study. The authors would like to express their gratitude to the technicians and staff of the Agricultural Research Council-Animal Production for their support.

Conflict of interest

The authors declare no conflict of interest.

Author details

Ennet Moholisa^{1*}, Lizelle Rheeders¹, Kealeboga Mosimanyana¹ and Phillip Strydom²

1 Agricultural Research Council-Animal Production, Irene, Centurion, South Africa

2 University of Stellenbosch, Stellenbosch, South Africa

*Address all correspondence to: moholisae1@arc.agric.za

IntechOpen

© 2025 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. 

References

- [1] Bohrer BM. Blood and blood constituents for meat processing. *Current Food Science and Technology Reports*. 2024;**2**(17):25. DOI: 10.1007/s43555-023-00015-3
- [2] Ronald C, Matofari WJ, Nduko JM. Antimicrobial resistance of *E. Coli* strains in ready-to-eat red meat products in Nakuru County, Kenya. *The Microbe*. 2023;**1**:100022. DOI: 10.1016/j.microb.2023.100022
- [3] Moholisa E, Mosimanyana K, Rheeders L, Seema P, Strydom P. Consumer purchase intent and willingness to pay for cow blood sausages in South Africa. In: *Proceedings of the International Congress of Meat Science and Technology (ICOMST 2023)*; 20-25 August 2023, Padua, Italy: Session-7__03__23. Padua, Italy: International Congress of Meat Science and Technology; 2023
- [4] Sosibe K. Cows: The sacred and the profane. In: *Mail and Guardian Magazine*. 2016. Available from: <https://mg.co.za/article/2016-04-07-cows-the-sacred-and-the-profane> [Accessed: 20 May 2025]
- [5] Seshoene M. Traditional African food in South Africa. In: *South African Tourism*. 2023. Available from: <https://www.southafrica.net/tz/en/travel/article/traditional-african-food-in-south-africa> [Accessed: 5 May 2025]
- [6] Silva FAP, Amaral DS, Guerra ICD, Dalmas PS, Arcanjo NMO, Bezerra TKA, et al. The chemical and sensory qualities of smoked blood sausage made with the edible by-products of goat slaughter. *Meat Science*. 2013;**94**(1):34-38
- [7] American Meat Science Association (AMSA). *Research Guidelines for* *Cookery, Sensory, Sensory Evaluation, and Instrumental Tenderness*. 2nd ed. USA: American Meat Science Association; 2016
- [8] Pliner P, Hobden K. Development of a scale to measure the trait of food neophobia in humans. *Appetite*. 1992;**19**:105-120. DOI: 10.1016/0195-6663(92)90014-W
- [9] SAS Institute I. *SAS® 9.4 Language Reference: Concepts*. 6th ed. Cary: North Carolina; 2016
- [10] Siegel S, Castellan NJ. *Nonparametric Statistics for the Behavioural Sciences*. 2nd ed. New York: McGraw-Hill; 1988
- [11] Snedecor GW, Cochran WG. *Statistical Methods*. 7th ed. IOWA, USA: The Iowa State University Press; 1988
- [12] Ares G, Varela P. Trained vs consumer panels for analytical testing: Fueling a long lasting debate in the field. *Food Quality and Preference*. 2017;**61**:79-86. DOI: DOI.10.1016/j.foodqual.2016.10.006
- [13] Zhang Y, Holman BWB, Ponnampalam EN, Kerr MG, Bailes KL, Kilgannon AK, et al. Understanding beef flavour and overall liking traits using two different methods for determination of thiobarbituric acid reactive substance (TBARS). *Meat Science*. 2019;**149**:114-119. DOI: 10.1016/j.meatsci.2018.11.018
- [14] Kerth CR, Miller RK. Beef flavor: A review from chemistry to consumer. *Journal of Science of Food and Agriculture*. 2015;**95**:2783-2798. DOI: 10.1002/jsfa.7204
- [15] Khan MI, Jo C, Tari MR. Meat flavor precursors and factors influencing flavor

precursors—A systematic review. *Meat Science*. 2015;**110**:278-284. DOI: DOI.org/10.1016/j.meatsci.2015.08.002

[16] Mascarello G, Pinto A, Rizzoli V, Tiozzo B, Crovato S, Ravarotto L. Ethnic food consumption in Italy: The role of food neophobia and openness to different cultures. *Food*. 2020;**9**(2):5-7. DOI: 10.3390/foods9020112

[17] Pieniak Z, Verbeke W, Vanhonacker F, Guerrero L, Hersleth M. Association between traditional food consumption and motives for food choice in six European countries. *Appetite*. 2009;**53**(1):101-108

[18] Johnson M. Food Neophobia. 2021. Available from: <https://www.sensorysociety.org/knowledge/sspwiki/Pages/Food%20Neophobia.aspx#:~:text=Type%20of%20Food%20neophobia,tend%20to%20reject%20unfamiliar%20foods> [Accessed: 15 June 2025]

Chapter 3

The Future of Diets with Customized Sensory Cues

Jie Yan and Gianni Corino

Abstract

Numerous studies have demonstrated that our senses play a significant role in shaping food perception, eating experiences, and overall food consumption. As a result, multisensory stimuli are increasingly being used in food manufacture and product development. Building on this understanding, there is growing potential to explore a novel approach to healthy eating based on individual sensory responses. InstaFood is a speculative design project that envisions a future where dietary intake can be influenced through the manipulation of food-related visual cues. By combining insights from perceptual science, social media image analysis, and digital fabrication technologies, InstaFood proposes a new approach to personalized eating for well-being. This concept integrates digital technology, sensory perception, and healthy eating to offer an innovative framework for future dietary practices.

Keywords: speculative design, future eating, digital fabrication, food perception, visual cues

1. Introduction

Dietary habits are a central determinant of human health, influencing physical health, mental well-being, and longevity. Despite numerous nutritional research, the global prevalence of diet-related health conditions still continues to rise. The World Health Organization reports that poor diet is now one of the leading risk factors for non-communicable diseases worldwide, including obesity, type 2 diabetes, cardiovascular disease, and certain cancers [1].

With the rapid development of digital technology, significant changes have occurred not only in food production but also in food consumption. The emergence of a wide range of smart devices and technological innovations has introduced new conveniences and created more opportunities to promote healthy eating. Mobile applications enable users to record daily meals and analyze nutrition intake; smart wearables can help for quantified diet and tracking real-time physical data; intelligent kitchenware can offer multiple dietary suggestions including food storage, choices, cooking, and so on.

Although these technological products offer more rational dietary guidelines that can help users to make more efficient and appropriate food decisions, it is still often

difficult for people to completely follow these suggestions, as health is only of many complicated aspects of food choice. Traditional approaches to promoting healthy diets have predominantly emphasized nutritional parameters, including calorie counts, nutrient ratios, and micronutrient adequacy. While these strategies provide valuable guidance, they often overlook the subjective willingness of individuals to adopt and sustain such dietary changes.

Considering that digital fabrication can tailor not only food recipes but also food appearance, it is reasonable to propose its use in modifying sensory perception as a means to influence and potentially alter eating behaviors. Human food experiences are inherently multisensory: we eat not only with our mouths but with our eyes, noses, ears, and even our sense of touch. The color of a beverage can alter its perceived sweetness; the crunch of a chip can enhance its freshness; the plating style of a dish can affect satiety. These sensory cues operate both consciously and subconsciously, shaping preference, portion size, and enjoyment.

Recent years have seen a growing interest in leveraging sensory science for product development and marketing. Food companies routinely optimize color, texture, aroma, and sound to increase consumer appeal. However, such experiments involving sensory modification have rarely been systematically applied to promote healthy eating. Recent advances in digital technology, particularly in data recording and analysis, intelligent algorithms, and customized production, now make it possible to imagine a future in which sensory cues are tailored to an individual's preferences, needs, and health goals.

The InstaFood speculative design project is situated within this emerging space. It proposes a system that uses visual manipulation, perceptual science, and digital fabrication to influence eating behavior in a personalized, health-oriented way. Drawing from social media food images and 3D printing techniques, InstaFood envisions a future where dietary well-being is not enforced through menu restriction, but encouraged through food perception and eating experience.

This chapter introduces a (speculative) personalized eating system for well-being, InstaFood, through the introduction of its proposed/establishment and operation, including statements of its scientific foundations, technological enablers, ethical considerations, and social impacts. It begins with a literature review of crossmodal perception on food consumption, then about personalized tech that can support InstaFood, then followed by demonstrating InstaFood as a detailed speculative design case study, illustrating an alternative development possibility of digital fabrication technology and a preferable way for eating well-being as well as possible social implications if such future comes true.

This chapter introduces InstaFood, a speculative personalized eating system designed to enhance dietary well-being. It outlines the system's conceptual foundations, its proposed modes of operation, and its broader implications, including the scientific principles, technological enablers, ethical concerns, and potential social impacts that underpin it. The discussion begins with a review of the literature on crossmodal perception in food consumption, followed by an examination of personalized manufacture technologies that could support the development of InstaFood. The chapter then presents InstaFood as a detailed speculative design case study, demonstrating both an alternative trajectory for digital fabrication technologies and a vision for promoting eating-related well-being. Finally, it reflects on the possible social consequences should such a future scenario materialize.

2. Sensory influences on eating

The role of sensory perception in shaping food choices and eating behavior has been widely documented in psychology, neuroscience, and food science [2]. While taste and smell are traditionally recognized as the primary drivers of food enjoyment, research increasingly shows that other senses, including vision, audition, and touch, play equally significant roles, often interacting in complex ways to form holistic eating experiences.

According to Schifferstein et al. [3], food exhibits a distinctiveness within the realm of material objects, primarily attributed to its multisensory nature encompassing a holistic engagement of the five fundamental senses. Derived from past eating experience, a confluence of sensory attributes, including taste, sound, smell, sight, and touch, recurrently converge and interweave to orchestrate an intricate symphony of sensory experiences that reciprocally modulate one another. For instance, hot coffee tends to have a more aromatic smell and a denser taste, crunching sound makes potato chips taste crispier and apples fresher, and so on.

2.1 Visual cues

Vision is often the first sense engaged when encountering food, and it can strongly influence expectations and perceived taste [4]. Using eyes to seek food is a basic instinct, even in modern times; the necessity to personally forage for sustenance has been supplanted by the convenience of procuring meals from commercial establishments, but the visual sense remains profoundly significant [5]. According to Spence [2], specific visual characteristics enable preliminary determinations regarding the edibility or toxicity, palatability, or aversion of comestibles prior to actual oral engagement. Furthermore, grounded in past experiential recollections and relevant knowledge, it can not only identify the types of food and roughly predict its flavor, but also to some extent estimate the freshness, ripeness, calories, and nutritional value of the food through subtle visual cues [6].

Elucidating this phenomenon, Spence et al. [5] expound that we have a response mechanism to simulate eating, which aims to inform the body to prepare to accept, digest, and absorb the food. When we receive a food-related cue, no matter if it is a visual message or a sound or smell, our brain initiates a simulated response of eating that food. Consequently, the olfactory perception of baking aromas leads to a conjecture of newly baked bread, while the observation of fresh lemons engenders a presage of tartness on the palate. Evidently, vision assumes a pivotal role in the gastronomic domain, just as the saying goes “We eat first with our eyes” [7].

Generally, the physical characteristics of the food itself, such as color and shape, are important clues to recognize its types, even without any tag information [8]. Subtle variations in color hue, gloss, and saturation can further provide information about the ripeness and freshness of fruits and vegetables. Moreover, changes in food color can influence flavor perception. For example, when yogurt was colored red without altering any other properties, it was perceived as strawberry-flavored and judged to taste sweeter (**Figure 1**) [9]. In addition, color could also influence the perception of quantity and size. Just as in the case of an equal quantity of candies, the amount containing multiple colors was perceived as less, leading individuals to consume more in comparison to the portion featuring a single color [10]. The energy and nutrition of food can also be perceived from food appearance to some extent, which helps people to eat smartly [5]. For instance, the traditional Japanese food culture indicates that a healthy meal should contain at least five colors [11].

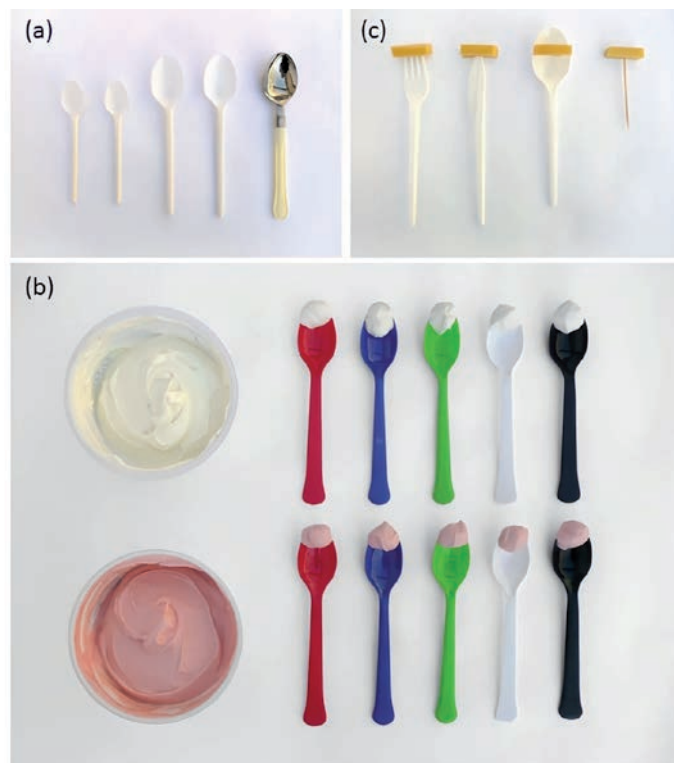


Figure 1.
The flavor experiment for yogurt by Harrar and Spence [9].

In addition, food presentation and the choice of serving container also play a significant role in shaping the food perception and the overall eating experience. These elements have the capacity to substantially influence perceptions and evaluations related to quantity, quality, flavor, appetite, emotional response, value, and price [9, 12, 13]. As Szocs and Lefebvre [14] note, food perception is often guided by heuristics that rely heavily on an individual's prior gastronomic experiences. While this heuristic processing enables perception to occur rapidly and holistically, it also renders the outcomes highly susceptible to a range of sensory cues associated with food presentation. Life experience and empirical research have shown a variety of these effects: for instance, arranging dishes according to Michelin-style plating can elevate culinary ratings; dishes with rich color combinations tend to be preferred by most respondents [15]; and esthetically, balanced presentations are consistently favored over asymmetrical or mass-plated arrangements [16]. Furthermore, presentation style can influence perceived quantity: food presented in a horizontally spread layout is often judged to be a larger portion than the same amount presented in a vertical arrangement (**Figure 2**) [14].

Similarly, visual cues provided by containers and utensils also exert a substantial influence on food perception. For example, the use of red tableware has been shown to enhance perceived sweetness, whereas blue tableware is more likely to increase perceived saltiness. Harrar et al. [17] demonstrated this effect using popcorn, and Harrar and Spence [9] replicated it with yogurt, obtaining consistent results. Container color can also alter flavor perception in other contexts:



Figure 2.
Food in horizontal and vertical presentation by Szocs and Lefebvre [14].

brown jars have been found to intensify the perceived strength of coffee flavor, while a greenish-yellow label can make beer appear more citrus-like and of higher quality [18]. Plate color further influences perceived portion size. For instance, blue tableware can make the quantity of food appear larger, an effect that was intentionally employed during the Great Depression in the United States in the so-called “Blue Plate Special,” which allowed restaurants to serve smaller portions without consumers noticing [18]. Red, by contrast, is strongly associated with fast food and unhealthy eating. This stereotype can affect consumption behavior, with studies showing that food served on red plates or alongside red decorations is consumed in smaller quantities compared to the same food presented on white or green plates (ibid). The shape and size of containers also have notable effects on food perception. Rounded shapes tend to enhance sweetness more than angular or sharp shapes (**Figure 3**) [19]. Plates with curved or crinkled designs can also increase the perceived portion size [20]. Even when the amount and arrangement of food remain constant, serving it on a smaller plate can make the portion appear larger [21].

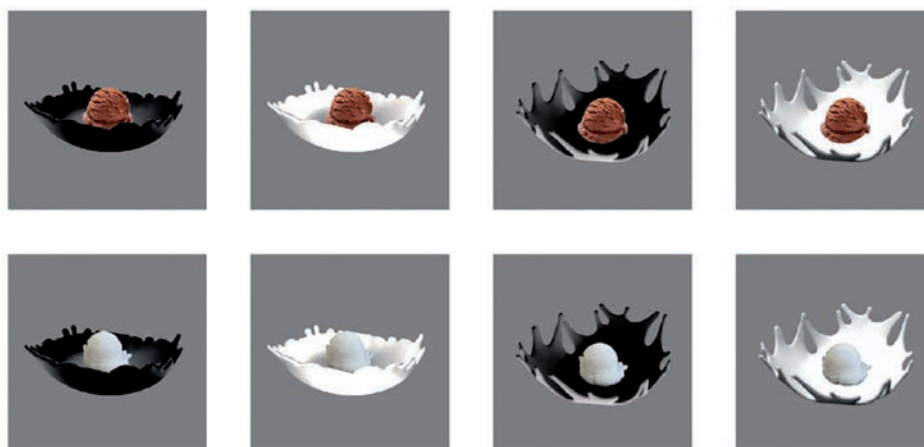


Figure 3.
Chocolate ice cream in smoother and pointier plates (top), lemon sorbet in smoother and pointier plates (down) by Chen et al. [19].

In contemporary digital culture, the visual dimension of food has been amplified by the proliferation of food photography on social media. Platforms such as Instagram not only serve as spaces for documenting daily meals and eating habits but also influence culinary trends, tastes, and even the design of menus and plating, which can change food cravings, choices, and consumption. As mentioned before, a kind of eating simulation can be triggered in the brain by food-related visual cues. Basso et al. [22] suggested that this simulation mechanism can be activated not only through direct sensory experience but also via mediated forms such as images or text. Building on this, Spence et al. [5] argued that the omnipresence of food imagery in digital media may increase food consumption, as heightened visual exposure can intensify eating simulation and Visual Hunger phenomenon. In such cases, the brain generates anticipatory signals, instructing the body to prepare for food intake and digestion. However, the opposite effect is also possible. Visual exposure can sometimes lead to Visual Satiation or Digital Satiation [5], whereby repeated viewing of food images diminishes the desire to eat. For example, Larson et al. [23] found that after participants viewed numerous photographs of savory snacks, their appetite for salty foods declined, resulting in a reduction in actual consumption. This effect is thought to occur because eating simulation can also produce a virtual sense of enjoyment and satisfaction, reducing the drive to consume the food in reality [5].

2.2 Olfactory and gustatory cues

Smell and taste are integral to the sensory experience of eating. Olfactory cues can also stimulate appetite prior to the commencement of a meal and are essential to flavor perception through the process of retronasal olfaction. For instance, the association of cake and bread would be produced by the sweet smell of baking, while citrusy smells can indicate relation to food and edibility, like coriander and beer. In contrast, medicinal odors are generally not associated with food-related perceptions [24]. Similar to the influence of visual cues, alterations in olfactory cues can modify flavor perception and affect actual food intake. For instance, increasing aroma intensity can enhance the perception of sweetness, enabling a reduction in sugar content without diminishing the overall sensory quality of the food [2].

2.3 Auditory cues

Sound is always the last sense that comes to mind when considering the impact of senses on the eating experience, but actually it also takes an important place, even plays a more significant role than we realize. The sounds we hear while we eat, even the murmurs of meal preparation, the clatter of product packaging, the blaring of environmental noise, or background music tempo, have all been shown to alter bite rate, meal duration, flavor perception, and even food choice. For instance, amplifying the sound of biting into a crisp snack increased perceived freshness; sharp sounds during food preparation made perceived quality reduce; loud sound of the product packaging bag can also increase the perceived crispness and taste experience of the chips [2].

2.4 Texture and tactile cues

Texture also plays a critical role in shaping food perception and the overall eating experience [2]. Emerging research in the interdisciplinary field of gastrophysics has

demonstrated that tactile sensations significantly influence taste experience. This influence extends beyond the texture of food itself, which affects mouthfeel, to include the tactile qualities of tableware, which shape handfeel. It can be seen that the entire tactile interaction should be considered. The textural properties of food, such as firmness, viscosity, and surface smoothness, not only determine mouthfeel but also convey impressions of freshness, quality, and satiety. For instance, smoother textures are often associated with heightened sweetness, aerated desserts can be perceived as lower in calories, and thicker liquids may enhance the perception of fullness. Moreover, because eating almost always involves utensils, the first sensory impression of food or drink is often mediated by touch through the hands. Consequently, modernist chefs, molecular mixologists, culinary artists, and even designers of packaging and tableware are paying increasing attention to the tactile dimensions of eating, from the material and weight of cutlery to its temperature and firmness. Some creative practitioners have intentionally incorporated textures into utensils, such as designing spoons with surface variations to heighten awareness of flavor and texture. Similarly, the use of heavier, higher-quality cutlery has been shown to make food appear more carefully prepared and even more expensive.

2.5 Multisensory integration

Sensory cues rarely operate in isolation, and crossmodal effects represent a defining feature of eating experiences. Among these, the “supra-additive responses” are widely acknowledged, although there remains no definitive consensus regarding the precise definition and interpretation of flavor formation. Furthermore, the scope, degree, and complexity of different sensory involvement continue to warrant further exploration ([25], p. 549). Supra-additive responses describe situations in which the integration of multiple sensory inputs produces a perceptual effect that exceeds the sum of the individual components [4]. In other words, when disparate sensory attributes are combined, they act synergistically to amplify flavor perception, thereby enhancing the overall eating experience. For instance, the concurrent use of visual and auditory cues has been shown to produce stronger effects on flavor perception than either modality alone [2]. Such findings highlight the potential of multisensory integration not only as a means of designing more pleasurable eating experiences but also as a promising approach to encourage healthier dietary behaviors.

2.6 Current applications in industry

The integration of sensory design into food production and marketing has become increasingly prominent. Food manufacturers and retailers recognize that sensory cues can strongly shape consumer perception, often beyond the actual nutritional or functional properties of the product. Visual design is one of the most widely applied strategies: packaging color, typography, and imagery are carefully selected to prime expectations of freshness, indulgence, or healthfulness [26]. Similarly, portion size illusions, such as smaller plates or slim glassware, have also been incorporated in both commercial and institutional food service settings to encourage lower consumption without reducing satisfaction [27].

Auditory branding is another avenue of sensory application. The distinctive crunch of certain snack foods is deliberately engineered to enhance perceptions of quality, while background music in retail or dining environments is used to guide

pacing, mood, and even menu choices [2]. Aromatic marketing, such as diffusing fresh bread scents in supermarkets, has been shown to increase purchase intentions and time spent shopping.

Despite these advances, most sensory strategies are deployed to maximize appeal and sales rather than to promote public health. This presents a critical opportunity to redirect sensory design toward interventions that encourage healthier consumption patterns, an ambition that speculative projects such as InstaFood seek to involve.

3. Technological foundations for customized sensory diets

The emergence of customized sensory diets is deeply intertwined with the rapid evolution of digital fabrication technologies, most notably 3D printing. In the culinary context, 3D printing—also referred to as additive manufacturing—has expanded from experimental applications in laboratories to practical uses in fine dining, healthcare, and even space exploration. Its distinctive advantages, including design flexibility, precision layering, and the ability to handle diverse edible materials, position it as a transformative enabler of personalized food systems [28, 29]. By integrating computational design with sensory science, these technologies open novel avenues for tailoring not only the nutritional content of food but also its sensory presentation, which is central to the speculative InstaFood project.

3.1 Digital fabrication in food production

3D food printing exemplifies the capacity to reshape how food is prepared, consumed, and experienced. Unlike conventional cooking methods that rely on subtractive processes, additive manufacturing builds structures layer by layer, enabling precise control over form, texture, and even flavor distribution. Researchers have demonstrated the feasibility of printing with chocolate, doughs, meat pastes, and hydrocolloids, each requiring careful calibration of viscosity, temperature, and structural stability [30]. Such versatility allows designers and chefs to replicate traditional foods, such as pizzas or pastries, with high fidelity while simultaneously innovating new culinary forms that would be impossible by hand (**Figure 4**) [31, 32].

Beyond replication, 3D printing has been applied to create futuristic culinary concepts. For instance, the Edible Growth project by Chloé Rutzerveld envisions food as semi-finished products that continue to grow after printing, giving consumers control over the timing of harvest and consumption [33]. Similarly, Open Meals' Sushi Singularity customizes sushi based on biometric data, offering hyper-personalized



Figure 4. *Typical potica cake (left) 3D printed potica cake concept visualization (centre) 3D printed jelly cake prototypes with a secret message (right) by Antlejš et al. [31].*

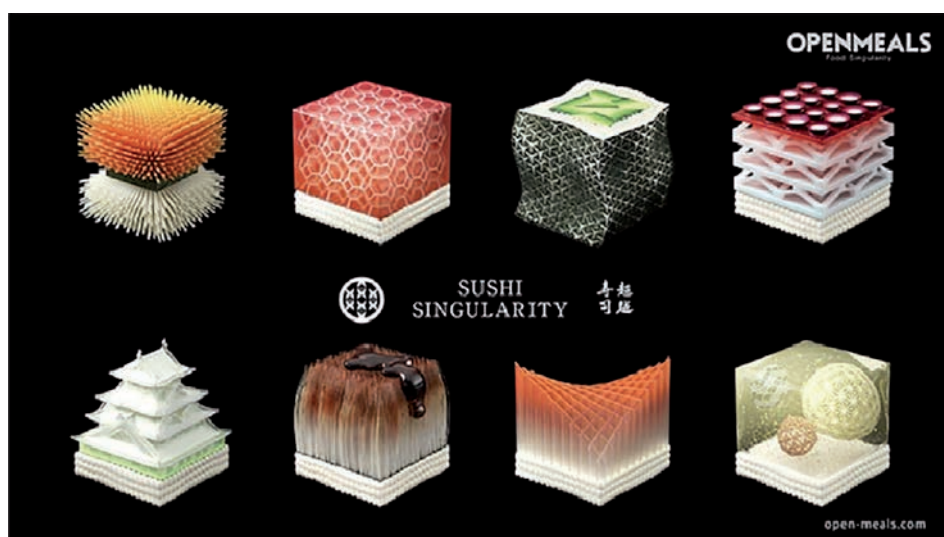


Figure 5.
Examples of Sushi Singularity by Open Meals.

nutrition alongside striking esthetic designs (**Figure 5**). Such cases highlight the dual potential of digital fabrication: to honor cultural traditions while simultaneously propelling radical innovation (**Figure 5**, https://www.open-meals.com/sushisingularity/index_e.html).

3.2 Applications for personalization and health

The adaptability of 3D food printing directly aligns with the goals of customized sensory diets. In healthcare, researchers have used 3D printing to produce texture-modified foods for patients with dysphagia, improving both nutritional intake and eating dignity. Similarly, the technology allows for nutrient-dense meals tailored to specific metabolic or medical requirements, such as diabetes-friendly formulations or protein-rich diets for the elderly [34]. The possibility of embedding sensory cues into these customized foods, such as visually enlarging portions to influence satiety, offers an additional layer of behavioral influence that extends beyond traditional nutritional interventions.

Importantly, digital fabrication also facilitates portion control and sustainable eating practices. For example, containers fabricated with predetermined caloric capacities (e.g., 500 kcal per plate) allow diners to visually calibrate their intake without the need for weighing [35]. Likewise, 3D-printed biodegradable or edible utensils, such as cookie spoons and coffee cups, integrate sustainability with sensory novelty. These developments illustrate the capacity of fabrication technologies not only to meet functional needs but also to enhance the multisensory dining experience.

3.3 Integration with digital intelligence

The power of digital fabrication is amplified when combined with artificial intelligence (AI), machine vision, and wearable technologies. Intelligent programs are developing the ability to collect and analyze food photos from personal social media archives, extracting information on food-related visual cues, such as food presentation, plating organization, plateware appearances, and viewing way.

By cross-referencing the data with metabolic indicators collected from wearables, algorithms can design personalized meals that balance nutritional adequacy with esthetic preferences. Once transmitted to a 3D printer, these designs can materialize as fully customized dishes, complete with tailored plating and containers. This convergence of visual data, health metrics, and fabrication creates a seamless feedback loop between the digital and physical dimensions of eating.

The future trajectory of this integration reflects broader industrial trends. Under Industry 4.0, automation drives efficiency and precision, envisioning kitchens where meals are algorithmically generated with minimal human intervention [36]. However, as Industry 5.0 gains traction, human-centricity becomes paramount. Rather than eliminating human involvement, technologies like 3D food printing are expected to collaborate with users, respecting subjective preferences and emotional needs while offering intelligent guidance [37, 38]. In this human-machine symbiosis, perceptual cues such as portion appearance or plating esthetics can be fine-tuned to align with individual desires for both health and pleasure.

Therefore, digital fabrication technologies, particularly 3D printing in food, represent more than novel cooking tools. They embody a shift toward intelligent, multisensory, and human-centric food systems that merge nutrition with perception. For projects like InstaFood, these foundations are critical: they allow for the materialization of speculative visions where visual cues not merely are decorative but also function as active agents in shaping dietary behavior.

4. A speculation of InstaFood

InstaFood is envisioned as a speculative design project that explores how food-related visual cues can be manipulated to influence dietary behavior. Building on insights from perceptual psychology, social media culture, and digital fabrication, the concept imagines a future in which personalized eating experiences are shaped by customized sensory interventions. Unlike conventional approaches to personalized nutrition that focus primarily on biochemical optimization, InstaFood emphasizes the perceptual and experiential dimensions of food.

4.1 Conceptual foundations

The project draws inspiration from two converging cultural and technological trajectories. First, contemporary food culture is dominated by visibility: the “Instagrammable meal” has become both a marketing tool and a form of self-expression. Food images influence not only social identity but also appetite and craving, often encouraging overconsumption or indulgence [39]. Second, digital fabrication and computational tools now make it possible to materialize visual concepts in physical form, blurring the boundary between the pixel and the plate.

InstaFood operates through a three-stage system:

1. **Image harvesting and analysis:** Users’ food preferences are inferred from social media archives, detecting recurring esthetics such as bright colors, symmetrical plating, or indulgent textures.
2. **Perceptual reframing:** These preferences are adjusted using principles from sensory psychology, for instance, intensifying the visual vibrancy of vegetables to increase appeal or resizing portions to influence satiety perception.

3. Materialization: Modified designs are fabricated through 3D printing at the dining table.

This framework transforms food images from passive media into active nutritional interventions, positioning InstaFood as a design probe for envisioning how eating might evolve when sensory manipulation becomes personalized and pervasive.

4.2 Speculative scenario

Within the envisioned future landscape, a personalized eating system named InstaFood will emerge. Analogous to current dietary applications, it can be installed on mobile devices, thereby affording users the flexible accessibility at their convenience. Users can also operate it directly via voice-activated communication, just similar to interactions with contemporary virtual assistants like Siri.

Users can directly tell InstaFood what they want to eat by voice. After receiving the instruction about what users want to eat, InstaFood will promptly engage in a search within its comprehensive standard recipe database. After reading the standard recipe in the system, it will analyze the nutritional composition and energy supply of the dish. After the analysis results are obtained, they are then compared with the nutritional requirements of the user. If a standard recipe is found to contain more nutrients and energy than the user needs, InstaFood will ask for the user's permission to personalize it according to the user's specified health goals.

This personalized modification of the recipe will consist of two parts, namely the food content and the food presentation. Similar to current smart dietary apps, InstaFood will analyze and calculate the appropriate food recipe for the user. At the same time, due to the recipe changes, the eating experience and satisfaction that should have been obtained will be affected. Therefore, InstaFood will also modify the presentation of food accordingly, trying to fill and solve this problem through Visual Diet, that is, using the influence that visual cues have on perception and experience to change actual intake.

Upon user authorization for InstaFood to optimize the recipe, the system will initiate an analytical process involving the user's body and biophysical data. This analysis encompasses parameters such as age, height, weight, body fat composition, metabolism, exercise expenditure, among others (**Figure 6**). Then, it will undertake calculations to determine the appropriate energy intake and nutrient content tailored to the user. The calculated values will then be compared with the nutritional parameters inherent in the queried standard recipe. This comparative analysis serves the purpose of ascertaining the gap between the user's food cravings and the individual's nutritional requirements (**Figure 6**) [40].

In accordance with identified gaps, a targeted objective for manipulating visual impact on perception can be established. For instance, if the lacuna pertains to curtailing sugar consumption, the corresponding objective for visual impact could be to heighten the perceived sweetness. Similarly, when the objective is to curtail overall energy intake, the visual impact goal may be directed toward amplifying the perception of quantity and portion size. To operationalize these objectives, algorithms can be deployed to scrutinize pertinent visual cues within the dataset derived from empirical investigations of psychological research delineating the visual impact on food perception and the overall eating experience.

The process of selecting particular influential visual cues relies on algorithmic analysis of user habits and preferences identified from Instagram photo posts.

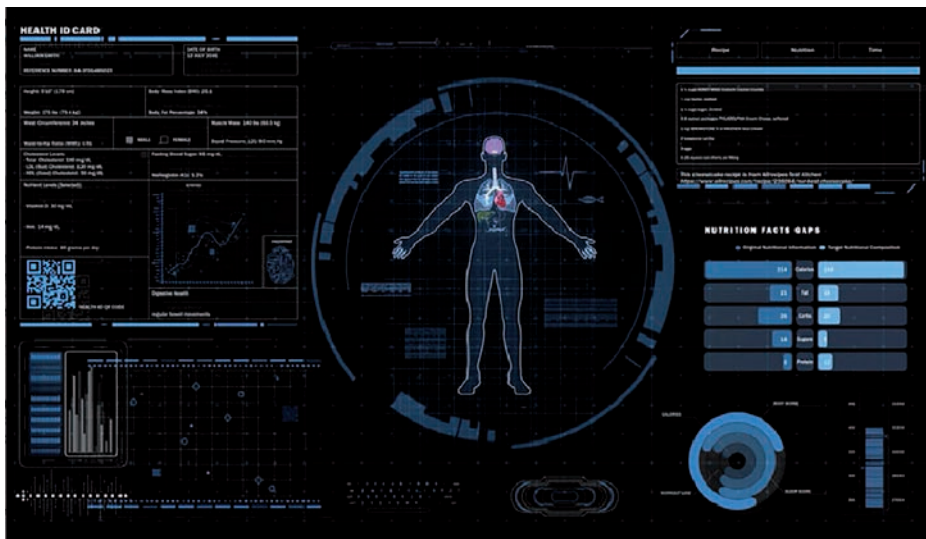


Figure 6.
User's body data analysis.

Firstly, InstaFood will read and collect all the images on the user's Instagram, filtering out the food images and creating the individual food image database. Then, InstaFood will further pick out the specific images of relevant dishes that the user expects.

After the food images of these specific dishes are collated, the relevant visual cues will be identified, extracted, and statistically analyzed (**Figure 7**). Through a process of calculation and deduction, the algorithms can ascertain the optimal visual cues and specific parameters that are most conducive for the user to consume that particular dish (**Figure 7**) [40].

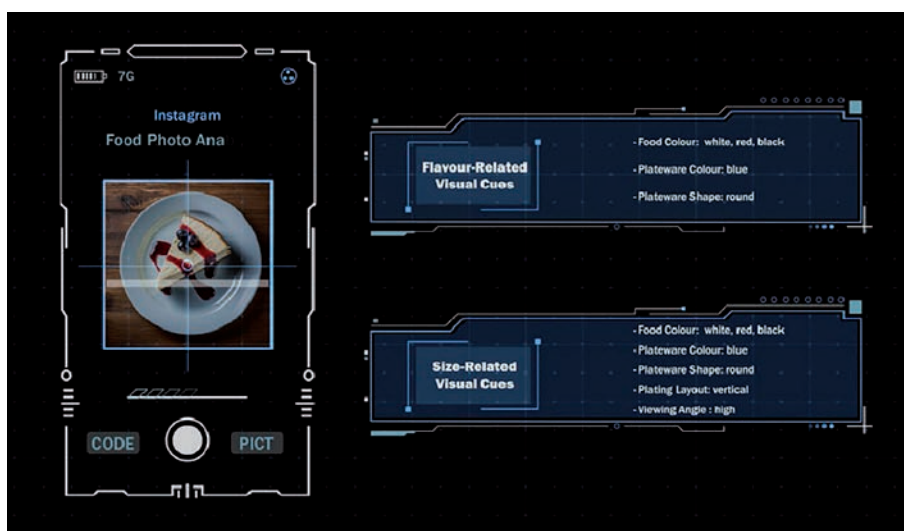


Figure 7.
Analysis of visual cues in food pictures.

To illustrate, consider a scenario in which a user expresses a desire for a cheesecake, but InstaFood finds that the high sugar content in the standard recipe surpasses recommended dietary limits. In response, the algorithms leverage insights gleaned from the visual impact psychological research dataset, specifically focusing on visual cues that influence the perception of sweetness and portion size, such as red and white coloration, round shape and smooth edges, a smaller container size, a horizontal plating layout, and so on. Subsequently, through statistical analysis of the user's relevant food images on platforms such as Instagram, the algorithms can discern user-specific preferences and habits, then infer the appropriate visual cues that are most influential. In this case, an optimal cheesecake should manifest as white in color, featuring a triangular shape with modest proportions. For its presentation, the cheesecake is recommended to be centrally positioned, employing a horizontal plating layout, and served on a diminutive round white plate, inclined at a 28-degree angle (**Figure 8**) [40].

Based on specific parameters, the algorithms will autonomously generate a model of the cheesecake and its accompanying plate. Following the receipt of this model, the responsibility for its materialization into a tangible entity lies with the 3D printer. During this phase, the user is required merely to await notification signaling the completion of the 3D printing process. After the cheesecake is printed, the user can serve it to the dining table and then enjoy the food (**Figure 9**) [40].



Figure 8.
Changed viewing angle.



Figure 9.
Presentation of cheesecake.

4.3 Features and social implications

In the forthcoming future of InstaFood, 3D printers will assume the status of commonplace kitchen appliances, analogous to the ubiquitous presence of microwaves in contemporary household. Compared to the current 3D printing technology, this technology will have a big improvement. It has the potential to simplify food from preparation to serving, by not only covering the cooking function but also making appropriate containers for food matching. With the development and progress of technology, 3D printing has the potential to solve this lack of cooking function in the future. For example, pancake 3D printers that can print and cook at the same time have already been developed in China, by replacing the printing platform with a pan capable of heating. For dishes with complex cooking steps, it might be possible to combine a 3D printer with a cooking robot. After the food is 3D printed, it can be processed by the cooking robot, and then people can get their food directly cooked and ready to eat.

In addition, this 3D printing method, which can directly convert raw materials into cooked food, can also standardize food production, cooking process, and other links to obtain unified and controllable taste enjoyment. At factory setup, each kitchen 3D printer can be installed and connected to a standardized recipe database. Users can directly search and choose their favorite dishes at the time of operation, without the involvement of steps from nutrition content to shape organization. That can greatly facilitate the food acquisition process and can also enhance the accessibility and user friendliness of the 3D printing process for an intuitive and simplified cooking experience.

As for the tableware, they will be made of biodegradable materials and produced with the food. Instead of printing food on the printer's work platform, 3D printers will follow the dish settings in the recipe program and place the food on the printed plateware directly, so not only will the food fabrication be programmed, but the food presentation will also be standardized. Additionally, because these 3D printed containers will be composed of environmentally friendly materials, they both align with ecological imperatives and furnish users with the added convenience of no need for post-meal dishwashing. This operational mode not only conserves water resources but also mitigates the environmental impact stemming from the production and transportation of conventional detergents. To some extent, this comprehensive strategy, encompassing both material selection and usage procedures, can contribute to sustainable development.

From a broader perspective, the entire process of food preparation, fabrication, and consumption is impending to change. People no longer need to make frequent trips to the store to buy fresh ingredients and spend space and resources to store and keep them in fresh. At that time, people only need to purchase different material powders regularly and fill them into the material tank, without any special conditions required for storage. So, refrigerators may be obsolete. In addition, the absence of requirements for washing, cutting, and cooking makes many kitchen appliances redundant, including cutting boards, knives, pots, stoves, ovens, and plates. Then, the demarcation between kitchen and dining room may also get blurred. Instead of complicated kitchen setups, people simply vacate a spot to place a 3D printer that autonomously executes the entirety of the food fabrication process. This innovative transition not only simplifies culinary endeavors but also fundamentally redefines the traditional notions associated with food fabrication.

4.4 Ethical considerations

One concern lies in the balance between nudging and manipulating. While altering visual cues to promote healthier eating may seem benign, it raises questions about consumer autonomy. To what extent should individuals be guided, consciously or unconsciously, toward particular dietary behaviors? Scholars in persuasive technology caution that such interventions must preserve informed choice and transparency [41].

Then, the use of social media imagery and biometric data to personalize meals introduces significant privacy concerns. Food choices are deeply personal, reflecting not only health but also identity, culture, and belief. Systems like InstaFood would need robust safeguards for data storage, consent, and control, ensuring that users—not corporations—retain ownership of their digital food identities.

Finally, InstaFood reflects broader shifts under Industry 5.0 toward human-centric technology [38]. Here, machines do not replace but collaborate with human creativity and preference. The dining table becomes a hybrid site where pixels and flavors meet, mediated by algorithms yet grounded in human pleasure and cultural meaning. This shift compels a reconsideration of the role of technology in daily life: not as an efficiency tool alone, but as a medium for shaping how we experience nourishment, care, and connection.

5. Conclusions

Looking ahead, the convergence of perceptual science, digital fabrication, and data-driven personalization suggests a radical reconfiguration of food systems. Speculative projects like InstaFood illuminate not just possible technologies but also the cultural and ethical frameworks within which eating might evolve. The future of personalized sensory diets lies in harnessing these innovations to support health and well-being while respecting human values and diversity.

The significance of this future extends beyond technology. Personalized sensory diets raise questions about how societies define health, pleasure, and authenticity in food. If eating becomes mediated by algorithms and perceptual manipulation, how will this reshape cultural traditions, social rituals, and personal agency? Industry 5.0 provides one possible answer: technologies designed not to replace but to collaborate with humans, foregrounding creativity, sustainability, and emotional well-being alongside efficiency.

Ultimately, the future of diets with customized sensory cues is less a matter of engineering perfect meals than of reimagining what it means to eat well in a technologically mediated world. By weaving together nutrition, perception, and design, projects like InstaFood provoke us to envision food not only as fuel but also as a multisensory medium for health, identity, and connection.

Author details

Jie Yan^{1*} and Gianni Corino²

1 East China University of Science and Technology, Shanghai, China

2 Univertiy of Plymouth, Plymouth, UK

*Address all correspondence to: yan.jie123@163.com

IntechOpen

© 2025 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. 

References

- [1] Alkandari A, Longenecker JC, Barengo NC, Alkhatib A, Weiderpass E, Al-Wotayan R, et al. The prevalence of pre-diabetes and diabetes in the Kuwaiti adult population in 2014. *Diabetes Research and Clinical Practice*. 2018;**144**:213-223
- [2] Spence C. *Gastrophysics: The New Science of Eating*. UK: Penguin; 2017
- [3] Schifferstein HN, Fenko A, Desmet PM, Labbe D, Martin N. Influence of package design on the dynamics of multisensory and emotional food experience. *Food Quality and Preference*. 2013;**27**:18-25
- [4] Small DM. Flavor is in the brain. *Physiology and Behavior*. 2012;**107**:540-552
- [5] Spence C, Okajima K, Cheok AD, Petit O, Michel C. Eating with our eyes: From visual hunger to digital satiation. *Brain and Cognition*. 2016;**110**:53-63
- [6] Auvray M, Spence C. The multisensory perception of flavor. *Consciousness and Cognition*. 2008;**17**:1016-1031
- [7] Delwiche JF. You eat with your eyes first. *Physiology & Behavior*. 2012;**107**:502-504
- [8] Spence C. On the psychological impact of food colour. *Flavour*. 2015;**4**:21
- [9] Harrar V, Spence C. The taste of cutlery: How the taste of food is affected by the weight, size, shape, and colour of the cutlery used to eat it. *Flavour*. 2013;**2**:1-13
- [10] Rolls BJ, Rowe EA, Rolls ET. How sensory properties of foods affect human feeding behavior. *Physiology and Behavior*. 1982;**29**:409-417
- [11] König LM, Renner B. Colourful = healthy? Exploring meal colour variety and its relation to food consumption. *Food Quality and Preference*. 2018;**64**:66-71
- [12] Zellner DA, Loss CR, Zearfoss J, Remolina S. It tastes as good as it looks! The effect of food presentation on liking for the flavor of food. *Appetite*. 2014;**77**:31-35
- [13] Zellner DA, Siemers E, Teran V, Conroy R, Lankford M, Agrafiotis A, et al. Neatness counts. How plating affects liking for the taste of food. *Appetite*. 2011;**57**:642-648
- [14] Szocs C, Lefebvre S. Spread or stacked? Vertical versus horizontal food presentation, portion size perceptions, and consumption. *Journal of Business Research*. 2017;**75**:249-257
- [15] Paakki M, Aaltojärvi I, Sandell M, Hopia A. The importance of the visual aesthetics of colours in food at a workday lunch. *International Journal of Gastronomy and Food Science*. 2019;**16**:100131
- [16] Velasco C, Michel C, Woods AT, Spence C. On the importance of balance to aesthetic plating. *International Journal of Gastronomy and Food Science*. 2016;**5**:10-16
- [17] Harrar V, Piqueras-Fiszman B, Spence C. There's more to taste in a coloured bowl. *Perception*. 2011;**40**:880-882
- [18] Spence C. Background colour & its impact on food perception and

behaviour. *Food Quality and Preference*. 2018;**68**:156-166

[19] Chen Y-C, Woods AT, Spence C. Sensation transference from plateware to food: The sounds and tastes of plates. *International Journal of Food Design*. 2018;**3**:41-62

[20] Spence C. “Mirror, mirror on the wall”: Can visual illusions be used to ‘trick’ people into eating less? *International Journal of Gastronomy and Food Science*. 2018b;**11**:31-34

[21] Wansink B, Van Ittersum K. Portion size me: Plate-size induced consumption norms and win-win solutions for reducing food intake and waste. *Journal of Experimental Psychology: Applied*. 2013;**19**:320

[22] Basso F, Petit O, Le Bellu S, Lahlou S, Cancel A, Anton JL. Taste at first (person) sight: Visual perspective modulates brain activity implicitly associated with viewing unhealthy but not healthy foods. *Appetite*. 2018;**128**:242-254

[23] Larson JS, Redden JP, Elder RS. Satiation from sensory simulation: Evaluating foods decreases enjoyment of similar foods. *Journal of Consumer Psychology*. 2014;**24**:188-194

[24] McGee H. *Nose Dive: A Field Guide to the World’s Smells*. London: Penguin Press; 2020

[25] Mattes RD. *Flavor and Feeding: Introduction to an International Conference*. Amsterdam, Netherlands: Elsevier; 2012

[26] Becker L, van Rompay TJ, Schifferstein HN, Galetzka M. Tough package, strong taste: The influence of packaging design on taste impressions and product evaluations. *Food Quality and Preference*. 2011;**22**(1):17-23

[27] Van Ittersum K, Wansink B. Plate size and color suggestibility: The Delboeuf illusion’s bias on serving and eating behavior. *Journal of Consumer Research*. 2012;**39**:215-228

[28] Jandyal A, Chaturvedi I, Wazir I, Raina A, Haq MIU. 3D printing—a review of processes, materials and applications in industry 4.0. *Sustainable Operations and Computers*. 2022;**3**:33-42

[29] Ngo TD, Kashani A, Imbalzano G, Nguyen KT, Hui D. Additive manufacturing (3D printing): A review of materials, methods, applications and challenges. *Composites Part B: Engineering*. 2018;**143**:172-196

[30] Godoi FC, Prakash S, Bhandari BR. 3d printing technologies applied for food design: Status and prospects. *Journal of Food Engineering*. 2016;**179**:44-54

[31] Antlej K, Leen R, Russo A. 3D food printing in museum makerspaces: Creative reinterpretation of heritage. *KnE Engineering*. 2017:1-7

[32] Lipton JI, Cutler M, Nigl F, Cohen D, Lipson H. Additive manufacturing for the food industry. *Trends in Food Science and Technology*. 2015;**43**:114-123

[33] Rutzerveld C. *Food Futures: How Design and Technology Can Reshape Our Food System*. BIS Publishers; 2018

[34] Baiano A. 3D printed foods: A comprehensive review on technologies, nutritional value, safety, consumer attitude, regulatory framework, and economic and sustainability issues. *Food Reviews International*. 2022;**38**:986-1016

[35] Zampollo F. *Meaningful eating: A new method for food design* [Doctoral]. UK: London Metropolitan University London; 2013

[36] Frank AG, Dalenogare LS, Ayala NF. Industry 4.0 technologies: Implementation patterns in manufacturing companies. *International Journal of Production Economics*. 2019;**210**:15-26

[37] Leng J, Sha W, Wang B, Zheng P, Zhuang C, Liu Q, et al. Industry 5.0: Prospect and retrospect. *Journal of Manufacturing Systems*. 2022;**65**:279-295

[38] Xu X, Lu Y, Vogel-Heuser B, Wang L. Industry 4.0 and industry 5.0—Inception, conception and perception. *Journal of Manufacturing Systems*. 2021;**61**:530-535

[39] Tiggemann M, Hayden S, Brown Z, Velissaris N. The effect of Instagram “likes” on women’s social comparison and body dissatisfaction. *Body Image*. 2018;**26**:90-97

[40] Yan J. #Instafood: A speculative design exploration of the eating experience, perception, fabrication, and consumption [Thesis]. University of Plymouth. 2024. DOI: 10.24382/1M8H-DS76

[41] Fogg BJ. *Persuasive Technology: Using Computers to Change What we Think and Do*. San Francisco, California, USA: Morgan Kaufmann; 2003

Chapter 4

Food Flavour Perception and the Measurement of Tastes and Smells

Sittiwat Lertsiri, Mutita Meenune and Wilatsana Posri

Abstract

Flavour perception of food is discussed in this chapter in two main stages of the sensory evaluation process: how flavour evokes our senses and how we measure flavour perception. Flavour stimuli are inherently complex due to the mixed nature of flavour compounds in food. Both the food matrix and individual human factors further modulate this perception. Factors influencing the identification and intensity of flavour stimuli in water- and alcohol-based food matrices are explained, linking subjective and objective sensory assessments with the instrumental measurements. Sensations are understood as raw data transmitted from our sensory receptors to the brain for processing. Flavour perception represents processed data, shaped by integration with memory and emotions related to the flavour and the food medium. When sensations are evoked by flavour stimuli, they are translated and formed in the mind through these cognitive processes. This chapter focuses on measuring flavour primarily through the senses of taste and smell. Traditional instrumental techniques such as HPLC and GC, as well as emerging machine-learning technologies like electronic nose (E-nose) and electronic tongue (E-tongue), which aim to mimic human flavour evaluation, are also presented and discussed.

Keywords: flavour in food, perceived flavour, odourants, tastants, GC-O, E-nose, E-tongue, flavour measurements, sensations, perception

1. Introduction

This book chapter brings together insights into flavour measurement drawn from our experiences as a sensory scientist and flavour chemists, gained through work with both international and local food industries.

The content will firstly establish a scope for how flavour stimuli are sensed and perceived in human subjects. We then present an alternative measurement scale as compared to the mainstream scaling method, including discussions on the practicality and complexity of measuring human perception. We also discuss the validity of responses from an implicit subjective measurement derived from emerging neuroscience approaches.

Then traditional and recent instrumental measurement tools, such as GC, HPLC, GC-MS, GC-O, the Electronic Nose as well as Electronic Tongue are presented, highlighting under what conditions these tools are optimal and how they are best used in order to validate sensory responses. The second focus of this chapter will also be on flavour perception and the flavour molecules responsible for key flavour notes in food ingredients.

2. Sensory science and human perception of flavour

Flavour is commonly explained as an integral sum of how aroma and taste are combined and perceived. We usually find the flavour term used interchangeably with taste in everyday conversations. People are not usually able to separate taste from aroma. If you would like to experiment how to do so, there is a simple and rather fun technique to distinguish the two senses, where the receptors of both senses can be temporally separated using a nose clipping trick whilst chewing strongly aromatic but bland-tasting food - all-flavour jellybeans are a good choice for demonstrating the differences of how these two senses are sensed, detected and perceived [1]. This, however, is not the way most of us taste our food (and not to be used with children or health-risk subjects!).

The field of sensory science has evolved considerably in understanding how we perceive and respond to these complex flavour experiences. When we conduct sensory evaluations, the fundamental distinction between objective and subjective measurements remains crucial for achieving reliable and meaningful results.

2.1 Understanding objective and subjective measurements

When we treat human subjects as consumers in sensory testing, we are not using them as precise measurement tools. Instead, we expect and welcome a wide range of responses; some people might love a product, whilst others hate it, even if they come from similar backgrounds. This variation in acceptance and pleasantness scores is not just normal, it is valuable for understanding consumer food choice.

However, when our goal shifts to measuring how intense a particular flavour characteristic actually is, not whether people like it, but how strong it truly is, we need consistency. This is where objective measurement comes into play. Quantitative Descriptive Analysis (QDA) using trained sensory panels is considered one [2–4]. These trained panellists can reliably assess intensity levels across different sensory attributes, supporting tasks in quality assurance, process optimisation, product reformulation, product benchmarking and product positioning. This is an ability that has proven invaluable in food business.

Recent developments have introduced what we call Rapid Sensory Descriptive Analysis methods. These use skilled panellists, experienced tasters or even naïve consumers to evaluate flavour profiles of the product range [5, 6]. It is particularly exciting how technology is now enhancing these evaluations, with new methods that mimic our human senses of smell, taste and vision to improve quality, consistency and safety assessments [7]. It's like having electronic assistants that can 'taste' alongside our human experts.

2.2 How we measure what people think and feel

For subjective measurements, we primarily rely on what people tell us through self-reported scales. Sensory scientists use all four types of measurement scales, but

the most popular is probably the 9-point hedonic scale. You have likely encountered this yourself. The scale runs from “dislike extremely” to “like extremely” with “neither like nor dislike” in the middle. It is simple and works well across different populations, including children as young as 9–11 years old [8].

One challenge we face is translation. The scale was developed and validated in English, so the descriptors do not always carry the exact same meaning in other languages [9]. It is a bit like trying to explain the difference between “nice” and “lovely” to someone learning English - the nuances matter. In practice, most sensory scientists treat the data as interval data and use parametric statistics, even though the scale categories are not truly equal intervals and lack a proper zero point. In some occasions, the data need to be standardised before analysis further [10–13].

The Magnitude Estimation Scale (MES) offers a different approach than the popular 9-point hedonic scale. Instead of fixed categories, we ask participants to rate intensity “in proportion” to a reference sample. Think of it like asking someone to rate how bright a light is compared to a standard bulb - if the standard is 100, how bright is this one? This generates what we call ratio data and provides much more detailed sensory information compared to fixed scales [3, 10, 12, 13]. MES works particularly well for quantifying taste intensities like sweetness and complements our instrumental measurements from techniques like Gas Chromatography (GC).

Spectrum Analysis, which combines MES with standard references, has assisted panel training and improved result consistency in limited training duration [3, 4, 12, 14]. The downside of using MES? All that numerical calculation and comparison can be mentally exhausting for the trained panellists, let alone ordinary consumers. Not everyone enjoys calculation especially whilst tasting food.

Apart from the measurement scale, we know that stimuli from food can change whilst in mouth during the eating process. This includes how trigeminal stimuli, such as the burn from chilli or the cooling sensation from mint, can modulate both flavour and mouthfeel perception [15, 16]. Eating experience is not a quick and still picture, it is a whole story.

2.3 The discovered world of unconscious responses

Beyond traditional self-reported scales, neuroscience is revolutionising how we understand flavour responses. Is it true that up to 95% of our purchasing decisions are made subconsciously [17]? We think we are being rational consumers, but our brains may have often already decided before we consciously realise it.

This has led to tools like the Implicit Association Test (IAT), which reveals how we unconsciously link flavours to emotions and positive or negative attributes [18, 19]. It is rather like word association, but for tastes and feelings. The challenge is that it is quite time-consuming as a test would require 5–12 minutes of rapid-fire responses to bypass conscious thinking of the participants. It also requires large sample sizes (hundreds of participants) for reliable results.

What is exciting is how artificial intelligence and neuroscientific methods are being integrated with traditional human sensory panels. This could well define the next generation of sensory science research [7, 19, 20]. We are essentially teaching computers to understand human taste and aroma perceptions whilst simultaneously learning more about how our own brains process flavour information.

There are still questions about test-retest reliability and how contextual factors influence results [19–21]. Cultural background plays a major role in these associations, too, raising questions about whether results reflect individual psychology or

broader cultural influences on flavour preferences and perceptions. A flavour that evokes comfort in one culture might trigger entirely different associations in another, take, for example, the case of fermented tofu or durian flavour.

2.4 How we learn to like (or dislike) flavours

Flavour learning is powerful. It is essentially about linking the taste and aroma of food with what happens afterwards. Eat something that makes you feel satisfied and energised, and you will likely crave it again. Experience nausea after eating something, and you'll probably develop an aversion that can last for years [1, 22].

The amygdala in our brain is the key player, connecting sensory experiences to emotional and behavioural outcomes. Flavour learning requires less mental effort and fewer experiences compared to other types of learning. Flavour perception is dynamic. It is constantly being updated by our experiences, with strong emotional tags (positive or negative) guiding future food choices. This explains why certain foods can instantly trigger feelings of comfort or disgust based on past experiences [23], even when the current sensory input is perfectly neutral. The nostalgic smell of your grandmother's cooking can instantly transport you back to childhood, or how a particular food might make you queasy because you once had food poisoning after eating it.

Recent research has provided insights into how various strategies and mechanisms can enhance food flavour perception, highlighting the complex interplay between our sensory systems and cognitive processing [24].

2.5 The biology behind what we taste and smell: Our complex taste system

Our taste system handles the five basic tastes: sweet, salty, sour, bitter, and umami (savoury, meaty taste). It all begins at taste receptors on taste buds in our mouth. Those little bumps on your tongue are papillae which gather many of taste buds on each bump. The taste bud each contains different types of taste receptor cells, each responding to specific taste stimuli.

G-protein-coupled receptors on surface of Type II cells detect bitter, sweet, and umami flavours [25–28]. Recent comprehensive studies have noted that whilst we understand sweet, bitter, and umami receptors pretty well, sour and especially salty taste receptors still need more investigation [25, 29]. The understanding of taste-receptor-diet mechanism is particularly important in a world full of High Fat, Salt and Sugar (HFSS) products.

Sour taste cells work differently, using ion channels rather than the G-protein system. The mechanisms for detecting salt are still being figured out. It is suggested that sodium-taste cells share some features with Type II cells but lack a key component called TRMP5 [28]. This makes them a unique subset, like a family member who shares some traits but has their own distinct characteristics. Interestingly, high salt concentrations can activate bitter and sour receptors, too, triggering what we call aversion pathways [25]. This might explain why extremely salty food does not just taste salty.

Recent neuroscience research has revealed detailed protein structures of taste receptors, like TAS2R14, which help us perceive bitter tastes [30]. Understanding these molecular details opens doors to possibilities for healthier food interventions, such as reformulating high-fat, salt and sugar foods without sacrificing taste appeal.

3. Our smell system: The dominant player of flavour

Smell is arguably the most crucial component of flavour perception, though most people do not realise just how dominant it is. Our brains can recognise hundreds of thousands of different odours simultaneously. It is an impressive capability that no other analytical instruments can beat.

Olfactory receptors, like many taste receptors, are G-protein-coupled receptors located on sensory neurons in the olfactory epithelium at the back of our nasal cavity. This location is crucial because it provides the shortest route to responsive brain functions, enabling those rapid reactions to odour stimuli that can trigger immediate memories or emotional responses [28].

Recent studies confirm what sensory scientists have long suspected: taste and smell are strongly linked. Olfactory receptors enhance flavour perception by sending signals to the brain, creating those rich, nuanced experiences we associate with different foods through what we call multisensory integration.

The integration of traditional sensory methods with advanced neuroscientific techniques and artificial intelligence represents where our field is heading. These developments promise to enhance our understanding of human flavour perception whilst maintaining what has always been central: the importance of actual human sensory evaluation. Sensory flavour perception is not only applied in food, personal care and pharmaceutical products but also applied in all other stuff we see, touch, smell, taste, hear and feel.

We will be exploring olfactory pathways further when we discuss instrumental procedures that mimic human perception – GC-O and electronic noses that attempt to replicate what we do naturally at the end of this chapter. The next section will examine how flavour stimuli behave in different food systems, including water-based and alcohol-based environments, using a case study of exotic syrup, building upon our understanding of these human sensory perception mechanisms.

4. Food ingredients: Flavour molecules and materials

Think of flavour molecules as the messengers between your food and your brain. In this section, we are going to explore how these tiny chemical messengers, tastants and odorants, behave in different conditions, particularly in water and alcohol-based solutions. We will use palm sugar as our example to demonstrate this complex journey from food stimuli to flavour perception, showing you exactly how what we measure in the lab connects to what you actually taste and smell.

4.1 Flavour compounds in water-based solutions

Flavour compounds in water solutions are typically both volatile organic compounds (VOCs) and non-volatile taste compounds. Those VOCs are restless molecules and are always ready to jump ship and float up to your nose. On the other hand, the non-volatile taste compounds prefer to stay dissolved, once interacting with our taste receptors, contributing to sweetness, bitterness, sourness, saltiness and umami.

The VOCs are like those friends who cannot sit still at a party. These small molecules evaporate easily, especially when things heat up or when the liquid becomes less viscous. The VOCs can evaporate and contribute to what we perceive as aroma

or off-flavours. Esters, for instance, are responsible for those lovely fruity notes, like ethyl butanoate giving you that unmistakable pineapple aroma. Ketones, on the other hand, bring us those rich, buttery, creamy notes. It is diacetyl creating that lovely buttery smell. Meanwhile, the non-volatile compounds are the steady, reliable types. They dissolve in water and interact with taste receptors, contributing to sweetness, bitterness, sourness, saltiness and umami [26, 31].

Sweet tastants come in three main varieties: natural sugars (glucose, fructose and sucrose - the classics), sugar alcohols (like sorbitol and xylitol that often pop up in sugar-free products) and artificial sweeteners (aspartame and saccharin, among others).

Bitter tastants are dominated by alkaloids - think caffeine giving you that morning wake-up call, quinine in your tonic water and theobromine in chocolate. You'll also find bitter peptides and phenolic compounds hiding in plants and beverages like tea and coffee.

Umami tastants - that savoury, meaty taste that makes everything more satisfying - come mainly from amino acids like glutamic acid and aspartic acid, plus nucleotides such as inosine monophosphate (IMP) and guanosine monophosphate (GMP).

Sour tastants are typically organic acids such as citric acid in your lemon, lactic acid in fermented foods, malic acid in apples and acetic acid in vinegar.

Salt tastants include not just regular table salt but also flavour enhancers like monosodium glutamate (MSG).

Understanding these molecular personalities helps us choose the right tools to measure them. For water-based food systems, High-Performance Liquid Chromatography (HPLC) is usually our go-to method because these tastants can be extracted using aqueous solutions. Several factors can significantly affect how these compounds behave. Temperature is crucial because warmer liquids are like more energetic dance floors, encouraging compounds to move around and release faster. Solubility matters too as less soluble compounds tend to migrate to the surface where they can escape more easily. Agitation (stirring or swirling) increases the surface area and gives compounds more opportunities to break free. Finally, the food matrix itself can either suppress or enhance flavour release. Fats and lipids, for example, can hold onto volatile compounds like a blanket, delaying their release [31, 32].

4.2 Flavour compounds in alcohol-based solutions

Now, let us step into the more complex world of alcoholic solutions such as beer, wine and spirits. Ethanol brings unique chemical properties that completely change how flavour compounds behave, and the results can be absolutely fascinating. Alcohol does not just dissolve water-soluble compounds like water does, but it also embraces a wide range of fat-soluble flavour compounds. This means flavour compounds in alcohol-based systems are often perceived as more intense and complex [31–34]. This is why flavour manufacturers often use ethanol-water mixtures in their formulations. The ethanol increases the solubility of non-polar (fat-soluble) compounds, creating those complex, layered aromas that make your favourite beverages so intriguing. Ethanol also lowers surface tension, which means volatile compounds can vapourise more easily and reach your nose or instrumental detectors more readily. This enhances retronasal aroma perception, the wonderful burst of flavour you get when you swallow [33]. At higher concentrations, ethanol can suppress taste sensitivity, particularly sweetness. It also interacts with proteins and tannins, altering mouthfeel and astringency. This explains why beers and wines deliver such diverse sensory

profiles, including those unique mouthfeel sensations that contribute to the overall flavour experience.

This is a particularly interesting bit, for polyphenolic compounds like tannins (those responsible for that puckering sensation you get from strong tea or red wine) normally bind with proteins in your saliva, creating precipitation and that dry, astringent mouthfeel. But ethanol disrupts this binding by changing how both tannins and proteins behave. As a result, alcoholic beverages often feel less astringent, especially at higher alcohol levels. The astringent sensation becomes smoother, more rounded rather than sharp [32, 34].

4.3 Impacts of heat process on flavour molecules

Heat can create magnificent new flavours, but it can also destroy delicate ones if you are not careful. We all know that hot foods tend to taste more aromatic and intense, partly because heat enhances retronasal stimulation and creates that lovely warming sensation in your mouth through thermal tactile effects [19, 27, 35]. But heat does much more than just warm things up. It fundamentally changes food matrices, altering texture, viscosity and emulsion structures, which directly affects how flavours are delivered and how long they persist in your mouth. Heat also generates new flavour compounds through several key reactions:

Maillard reactions are perhaps the most famous actions. These occur when amino acids meet reducing sugars under heat, forming melanoidins and complex volatiles that give us those roasted, nutty, meaty and caramel flavour notes that make bread crust so irresistible.

Caramelisation happens when sugars break down under heat, creating both sweet and bitter compounds that produce those characteristic sweet, burnt, toffee and bitter notes we associate with caramel.

Lipid oxidation occurs when unsaturated fats get oxidised to aldehydes or ketones, which can produce rancid, grassy, fatty and green flavour notes. They are not always desirable, but sometimes part of the intended flavour profile.

Thermal degradation of vitamins and pigments can break down natural flavour compounds, sometimes generating off-flavours or creating dull, cooked tastes.

The relationship between temperature and aroma intensity is quite straightforward. Higher temperatures generally mean stronger perceived aromas because heat promotes the evaporation of volatile compounds. Heat also reduces the solubility of some compounds in food matrices, making them more available for detection by your sensory receptors. It disrupts non-covalent interactions (like protein-flavour or starch-flavour complexes), freeing up flavour molecules that were previously bound up. However, there's a flip side because heat can also destroy or drive off sensitive aroma compounds, particularly those delicate floral and fruity esters that give foods their subtle, refined notes [31, 32].

4.4 Case study of palm syrup: A flavour transformation journey

Let us bring all these concepts together with an example that perfectly demonstrates how food matrices and processing conditions affect flavour development. Palm syrup, made from the sap of the Palmyra palm (*Borassus flabellifer*), offers a case study in flavour transformation. The journey (**Figure 1**) begins with fresh palm sap, a relatively simple starting material that undergoes complex changes through heat processing. First, the sap is heated to create pasteurised palm sap.



Figure 1.
Palm sap production and its products.

It is at this point that the fresh, delicate flavours are lost and cooked flavours begin to form. The syrup then undergoes heat evaporation for several hours, concentrating the sugars whilst developing complex flavours and aromas through heat-driven reactions. This is where things get really interesting from a flavour science perspective. Those browning reactions such as Maillard and caramelisation reactions occur at boiling temperatures, fundamentally changing both the colour and flavour of the raw material. The result is a unique combination of sweetness and complex flavour notes.

Here is a perfect example of how processing conditions affect the final product: quick-heated palm syrup tends to display a lighter, yellowish colour with less flavour development, whilst slow-heated syrup develops a dark reddish-brown colour with intense, complex flavours. The high temperatures also accelerate sucrose inversion, where sucrose breaks down into glucose and fructose, fundamentally changing the sugar composition. These individual sugars can be detected and quantified using HPLC as tastants, whilst the volatile flavour compounds formed during heating can be analysed using Gas Chromatography (GC) [32].

The volatile flavour compounds in heated palm sugar syrup are formed mainly through Maillard and caramelisation reactions, which include furans, pyrazines, ketones, acids, aldehydes and phenols. The non-volatile compounds include various sugars (glucose, sucrose, fructose, and maltose), organic acids (acetic, formic, lactic, citric and malic acids), phenolic compounds (gallic, caffeic, ferulic and coumaric acids) and various Maillard reaction products.

This palm syrup example clearly illustrates the complexity of flavour stimuli in food matrices and demonstrates how environmental factors, in this case, temperature and processing time, have affected the concentration and types of flavour compounds present, ultimately influencing flavour perception. It also shows us why choosing appropriate instrumental methods for analysis is so crucial. We need techniques that can capture both the volatile and non-volatile compounds that contribute to the complete flavour profile.

5. Detection and measurement of flavour compounds

Now we understand how flavour molecules behave in different environments. To bridge the gap between what happens in your mouth and what happens in the laboratory, we are essentially trying to build instruments that can “taste” and “smell” the way you do.

The challenge is complex: how to create such instruments that can replicate the incredible sensitivity and sophistication of human sensory perception? As discussed earlier, our sensing organs, especially for ‘smell’, can detect compounds at unimaginably low concentrations and recognise hundreds of thousands of different odours [36].

5.1 Flavour sensing and human receptors

As mentioned earlier, flavour perception integrates three types of sensations: taste from your gustatory system, aroma from your olfactory system and those tactile sensations from your somatosensory system (e.g. hot, burn) sensations [37].

When you bite into a piece of hard candy: as you chew and it dissolves, the food structure breaks down and releases chemical molecules from the food matrix. The tastants, those water-soluble, small molecules, get dissolved in your saliva and make their way to your taste buds. When they find the right receptor proteins on taste receptor cells, they bind like a key fitting into a lock. The better the fit and the more molecules that bind, the stronger the signal sent to your brain via the chorda tympani, glossopharyngeal and vagus nerves.

Looking at instrumental analysis, to mimic this process, we need to replicate not just the chemical environment, but also the physical conditions. This means proper homogenisation and extraction in aqueous solvents, sometimes even using enzymes similar to those in saliva to mimic the mastication process [38]. Then we can use techniques like HPLC for highly specific detection of individual tastants, or electronic tongues that create patterns from arrays of chemical sensors. It is rather like having multiple taste buds working simultaneously.

The aroma side of things is equally fascinating but more complex. Those volatile aroma molecules, small, somewhat hydrophobic compounds, easily escape from the aqueous environment in your mouth into the air. When you breathe out after swallowing, these molecules travel through your oral cavity to your olfactory epithelium via what scientists call the retronasal route. It’s different from the orthonasal route when you simply sniff something directly [39].

To replicate this in the laboratory, we homogenise samples in solutions that mimic saliva conditions, by matching the pH and sometimes adding saliva enzymes. We then use headspace techniques that allow only the volatile molecules to be introduced into our analytical instruments, particularly Gas Chromatography (GC). Dynamic headspace techniques are even better at mimicking real breathing because they use clean inert gases like nitrogen to carry the molecules, just as your breath carries aroma molecules to your nose.

Your olfactory system is remarkable, it can differentiate more than 400,000 different odours due to the wide variety of odorant binding sites on receptor proteins, coded by more than 350 genes [37]. This is why creating instruments with comparable sensitivity and range requires such sophisticated detector arrays and advanced signal processing.

5.2 Detection of odorants and tastants: The instrument

5.2.1 Gas chromatography: The aroma detection

Since aroma molecules must be volatile to reach your olfactory receptors, it makes perfect sense that Gas Chromatography became our go-to technique for aroma analysis. Think of GC as a molecular sorting system with three main components: an injection port that converts liquid samples to vapour, a separating column that acts like a molecular obstacle course and a detection system that identifies what comes out the other end [40].

The real art lies in sample preparation and Static headspace techniques have been popularly applied and proven to be fundamentally essential. The techniques simply let volatile molecules accumulate above a food sample in a closed container, and they are then amenable to separation and subsequent detection. However, they do not really match real-life consumption conditions. It is more like leaving food sitting in a sealed jar then sniffed, rather than actually eating it.

More sophisticated approaches use tools like Solid-Phase Microextraction (SPME) and Stir Bar Sorptive Extraction (SBSE), which concentrate volatile compounds on specially coated surfaces before releasing them into the GC. These can enhance detection of the GC system [38, 41]. Dynamic headspace techniques are even better at mimicking actual eating because they continuously purge the sample with inert gas and trap the volatile compounds, much like the continuous process of breathing and tasting [39, 41, 42].

The crucial point is when odour-active compounds exist at extremely low concentrations in food (parts per billion to parts per trillion). Your nose can detect some compounds at these trace levels, so our instruments need to be substantially sensitive [31].

5.2.2 Odour activity values: The impact calculator

Not all volatile compounds are created equal when it comes to aroma impact. This is where the Odour Activity Values (OAV) concept comes in to bridge instrumental analysis with human perception. You calculate OAV by dividing the measured concentration of a compound in your food sample by its odour detection threshold in humans [43]. If the OAV is greater than one, that compound is classified as ‘odour active’, meaning it actually contributes to what you smell and taste.

It could be said to be a relevance filter for your analytical results. You might detect hundreds of volatile compounds, but only those with significant OAVs are likely to influence the actual eating experience.

5.2.3 Gas chromatography-Olfactometry: The human-instrument partnership

This is where things get really interesting. GC-Olfactometry (GC-O) creates a unique partnership between human perception and instrumental analysis. As volatile molecules exit the GC column, the flow splits - some goes to the instrumental detector, whilst the rest goes to a ‘sniff port’ where trained panellists literally smell what’s coming out [44].

These human “detectors” record three key parameters: when they smell something (retention time), what it smells like (odour attributes) and how strong it is (intensity). The result is an “aromagram” that reveals not just what volatile compounds are present, but which ones actually contribute to the aroma profile you perceive.

This technique illustrates need of human and instrumental analysis - machines can detect, identify and quantify, but humans provide the crucial link to actual sensory experience.

5.2.4 High-performance liquid chromatography: The taste analyser

For non-volatile tastants, those compounds responsible for sweet, salty, sour, bitter and umami sensations, HPLC is our primary tool. Unlike GC, which works with vapourised samples, HPLC separates compounds in liquid phase, making it perfect for those water-soluble tastants that dissolve in your saliva [32].

The beauty of HPLC lies in its versatility. Different column types can separate different classes of compounds, whilst various detectors (UV/Vis, fluorescence, mass spectrometry) can identify and quantify them with high accuracy. The key to success is matching your analytical conditions to your food matrix and target compounds.

5.3 E-tongue and E-nose: The digital sensory panel

5.3.1 Electronic tongues: Arrays of artificial taste buds

Electronic tongues represent a fascinating approach to taste analysis, instead of trying to identify individual tastants like HPLC does, they use arrays of low-selectivity chemical sensors that respond to multiple compounds simultaneously [45]. It provides a collection of artificial taste-buds with different but overlapping sensitivities.

The International Union of Pure and Applied Chemistry defines an electronic tongue as ‘an analytical instrument comprising an array of nonspecific, low-selective, chemical sensors with high stability and cross-sensitivity to different species in solution’ [45]. The magic happens in the data processing, where sophisticated statistical methods like multivariate analysis and pattern recognition create unique taste profiles for different samples. Bear in mind that samples analysed by this method need to be prepared in liquid form, where tastants get dissolved and can therefore be detected.

Three main sensing techniques dominate: potentiometry (measuring electrical potential), voltammetry (measuring electron transfer during chemical reactions) and impedance spectroscopy (measuring electrical resistance changes) [46, 47]. Each has its strengths, but voltammetry is particularly popular due to its simplicity, robustness and ability to generate large amounts of data [48].

5.3.2 Electronic noses: Digital olfaction

Electronic noses work on similar principles but focus on volatile compounds. They use sensor arrays to detect and classify complex aroma profiles, creating unique ‘smellprints’ that can be compared against databases using machine learning algorithms [31].

The advantages are persuasive: they can process large sample volumes in automated, high-throughput environments; they are not influenced by personal preferences or physiological conditions; and they provide objective, reproducible results. However, they are better suited for screening and quality control than for the detailed aroma compound identification that GC-O provides.

5.4 Bringing it all together: The practical approach

In flavour analysis, neither sensory evaluation nor instrumental analysis alone tells the complete story; we need both, but we need to use them strategically.

The most practical approach starts with screening using whichever method is the most convenient for your situation. If dealing with numerous samples and suspect quality issues, electronic noses or tongues can rapidly flag problems. When investigating specific off-flavours, GC-mass spectrometry might be your first port of call. Then we confirm and validate our findings with the complementary approach such as GC-O.

The ultimate goal is developing robust correlations between instrumental and sensory data. When we can reliably predict sensory responses from instrumental measurements, we can substantially reduce the workload on sensory panels whilst maintaining the connection to human perception that makes flavour analysis meaningful.

This integrated approach is particularly valuable for applications like shelf-life prediction, quality control and product development, where you need both the objectivity of instrumental analysis and the relevance of human sensory experience.

The field continues to evolve rapidly, with advances in sensor technology, data processing and our understanding of human sensory perception driving new possibilities for flavour analysis. Successful flavour analysis remains about bridging the gap between chemistry and human experience. The understanding is not just what are in the food, but how they make us feel when we eat it.

6. Conclusion: The future of sensory in flavour science

The measurement of flavour perception relies on human sensation, influenced by emotional and physical conditions. Instrumental analysis objectively detects flavour molecules objectively. **Figure 2** offers a simplified overview of how these subjective and objective approaches are integrated to quantify flavour perception. Achieving accurate and reproducible results, however, requires careful attention to factors

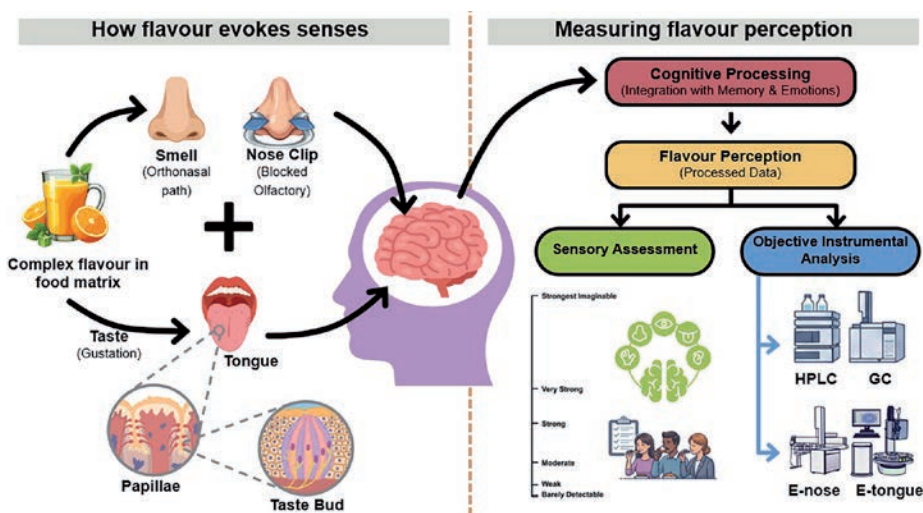


Figure 2.
Subjective and objective measurements of flavour perception.

such as sample preparation, instrument calibration, method standardisation, and sensitivity maintenance.

For flavour analysis purposes including exotic food investigation, flavouring ingredient development, process improvement, quality control, off-flavour problem-solving or commercial disputes, using only human responses or instrumental analysis alone can prove inadequate. However, maintaining both analytical approaches constantly is costly and time-consuming.

The practical solution involves screening with whichever method is the most convenient, then confirming results with the complementary approach. This reduces sample numbers requiring both analyses. When inter-correlations between analyses are well-defined, running only the convenient method becomes reasonable.

Since outputs are numerical, the sensory QDA data, chemical analysis concentrations, chromatogram peak areas, GC-O dilution factors, electronic sensor signals and simple correlations can be calculated and interpreted. Multivariate statistical analysis on both datasets creates predictive models which can forecast flavour changes and estimate shelf-life without continuous sensory analyses. This instrumental approach reduces trained panellist workload and shorten development timelines.

This is a rapidly evolving field, offering increasingly sophisticated methods for understanding complex relationships between food chemistry, sensory perception and consumer behaviour. Yet at its heart, sensory science remains fundamentally about human experience and about understanding what makes food appealing, memorable and satisfying to real people in real situations.

Thanks

The authors would like to thank Harper Adams University, Research Division for funding the publication fee.

Author details

Sittiwat Lertsiri¹, Mutita Meenune² and Wilatsana Posri^{3*}

1 Faculty of Science, Department of Biotechnology, Mahidol University, Bangkok, Thailand

2 Flavor Unit, Faculty of Agro-Industry, Prince of Songkla University, Hat Yai, Thailand

3 Harper Food Innovation, Harper Adams University, Newport, UK

*Address all correspondence to: wposri@harper-adams.ac.uk

IntechOpen

© 2025 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. 

References

- [1] Holmes B. Flavour: A User's Guide to our Most Neglected Sense. London: WH Allen; 2017. 310 p. ISBN: 9780753555903
- [2] Sensory Evaluation Division of the Institute of Food Technologists (IFT) cited in Editorial Message. Advances in sensory science: From perception to consumer acceptance. *Journal of Food Science*. 2023;**88**:A2-A4. DOI: 10.1111/1750-3841.16540
- [3] Lawless HT, Heymann H. Sensory Evaluation of Food: Principles and Practices. 2nd ed. London: Springer; 2010. 596 p. ISSN 1572-0330
- [4] Stone H, Bleibaum RN, Thomas HA. Sensory Evaluation Practices. 5th ed. London: Elsevier Science; 2020. 480 p. ISBN 0128153342, 9780128153345
- [5] Delarue J. Flash profile, its evolution and uses in sensory and consumer science. In: Delarue J, Lawlor JB, Rogeaux M, editors. *Rapid Sensory Profiling Techniques and Related Methods: Applications in New Product Development and Consumer Research*. Cambridge: Elsevier Ltd; 2015. pp. 121-152. ISBN: 9780081013328
- [6] Marques C, Correia E, Dinis L-T, Vilela A. An overview of sensory characterization techniques: From classical descriptive analysis to the emergence of novel profiling methods. *Food*. 2022;**11**(3):255. DOI: 10.3390/foods11030255
- [7] Rodrigues SSQ, Dias LG, Teixeira A. Emerging methods for the evaluation of sensory quality of food: Technology at Service. *Current Food Science and Technology Reports*. 2024;**2**:77-90. DOI: 10.1007/s43555-024-00019-7
- [8] Chen AW, Resurreccion AVA, Paguio LP. Age appropriate hedonic scales to measure food preferences of young children. *Journal of Sensory Studies*. 1996;**11**(2):141-163. DOI: 10.1111/j.1745-459X.1996.tb00038.x
- [9] Yeh LL, Kim KO, Chompreeda P, Rimkeeree H, Yau NJN, Lundahl DS. Comparison in use of the 9-point hedonic scale between Americans, Chinese, Koreans, and Thai. *Food Quality and Preference*. 1998;**9**(6):413-419. DOI: 10.1016/S0950-3293(98)00028-7
- [10] Pimentel TC, Gomes da Cruz A, Deliza R. Sensory evaluation: Sensory rating and scoring methods. In: *Encyclopedia of Food and Health*. Oxford: Elsevier, Academic Press imprint; 2016. pp. 744-749. DOI: 10.1016/B978-0-12-384947-2.00617-6
- [11] Wichchukit S, O'Mahony M. The 9-point hedonic scale and hedonic ranking in food science: Some reappraisals and alternatives. *Journal of the Science of Food and Agriculture*. 2015;**95**(11):2167-2178. DOI: 10.1002/jsfa.6993
- [12] Meilgaard MC, Civille GV, Carr BT. *Sensory Evaluation Techniques*. 5th ed. Boca Raton: CRC Press; 2015. 630 p. DOI: 10.1201/b19493
- [13] Kalva JJ, Sims CA, Puentes LA, Snyder DJ, Bartoshuk LM. Comparison of the hedonic general labeled magnitude scale with the hedonic 9-point scale. *Journal of Food Science*. 2014;**79**(2):S238-S245. DOI: 10.1111/1750-3841.12342
- [14] Pereira CT, Pereira DM, Bolini HM. Dynamic sensory profile of mango skyr yoghurt added of prebiotic and natural sweeteners: Multiple time-intensity

analysis and temporal dominance of sensations. *International Journal of Food Science and Technology*. 2021;**56**(8):4159-4169. DOI: 10.1111/ijfs.15045

[15] Toontom N, Meenune M, Aguiar KL, Posri W. Exploring hotness and pungent odour thresholds among three groups of Thai chilli users. *International Journal of Food Science and Technology*. 2024;**59**(11):8473-8489. DOI: 10.1111/ijfs.17177

[16] Saint-Eve A, Dél  ris I, Feron G, Ibarra D, Guichard E, Souchon I. How trigeminal, taste and aroma perceptions are affected in mint-flavored carbonated beverages. *Food Quality and Preference*. 2010;**21**(8):1026-1033. DOI: 10.1016/j.foodqual.2010.05.021

[17] Appinio. Implicit Association Testing (IAT) [Internet]. 2022. Available from: <https://www.appinio.com/en-gb/blog/market-research/implicit-association-test> [Accessed: June 7, 2025]

[18] Connors S, Spangenberg K, Perkins AW, Forehand M. Crowdsourcing the implicit association test: Limitations and best practices. *Journal of Advertising*. 2020;**49**(4):495-503. DOI: 10.1080/00913367.2020.1806155

[19] He W, de Wijk RA, de Graaf C, Boesveldt S. Implicit and explicit measurements of affective responses to food odors. *Chemical Senses*. 2016;**41**:661-668. DOI: 10.1093/chemse/bjw068

[20] Hao Z, Li H, Guo J, et al. Advances in artificial intelligence for olfaction and gustation: A comprehensive review. *Artificial Intelligence Review*. 2025;**58**(10):306. DOI: 10.1007/s10462-025-11309-4

[21] Stasia A, Songab G, Maurib M, Ciceri A, Diotallevi F, Nardonea G, et al.

Neuromarketing empirical approaches and food choice: A systematic review. *Food Research International*. 2018;**108**:650-664. DOI: 10.1016/j.foodres.2017.11.049

[22] Guichard E. Interaction of aroma compounds with food matrices. In: Parker JK, Elmore JS, Methven L, editors. *Flavour Development, Analysis and Perception in Food and Beverages*. Cambridge: Elsevier Ltd; 2016. pp. 273-296. ISBN: 9780081013823

[23] Rozin P, Haidt J, McCauley CR. Disgust: The body and soul emotion. *Handbook of Cognition and Emotion*. 1999;**429**:445

[24] Huang L, Dai Y, Zhang F, Zhang L, Zheng B, Zhang Y. Insights into the enhancement of food flavour perception: Strategies, mechanism and emulsion applications. *Food Science and Human Wellness*. 2024;**13**(5):2410-2424. DOI: 10.26599/FSHW.2022.9250199

[25] Ohmoto M, Jyotaki M, Foskett JK, Matsumoto I. Sodium-taste cells require Skn-1a for generation and share molecular features with sweet, umami, and bitter taste cells. *ENeuro*. 2020;**7**(6):1-12. DOI: 10.1523/ENEURO.0385-20.2020

[26] Diepeveen J, TCW M-P, van der Leij FR. Molecular insights into human taste perception and umami Tastants: A review. *Journal of Food Science*. 2022;**87**(4):1449-1465. DOI: 10.1111/1750-3841.16101

[27] Marsili R. Comparing sensory and analytical chemistry. In: Marsili R, editor. *Sensory-Directed Flavor Analysis*. London: CRC Press; 2019. pp. 1-22. ISBN: 9781574445688

[28] Simpson KL. Chapter 23 olfaction and taste. In: Haines DE,

- Mihailoff GA, editors. *Fundamental Neuroscience for Basic and Clinical Applications*. Philadelphia: Elsevier; 2018. pp. 334-345. DOI: 10.1016/B978-0-323-39632-5.00023-2
- [29] Li M, Zhou X, Wang J. Taste and its receptors in human physiology: A comprehensive look. *Food Frontiers*. 2024;**5**(3):1123-1145. DOI: 10.1002/fft2.407
- [30] Tao L, Wang D, Yuan Q, et al. Bitter taste receptor TAS2R14 activation and G protein assembly by an intracellular agonist. *Cell Research*. 2024;**34**:735-738. DOI: 10.1038/s41422-024-00995-4
- [31] Reineccius G. *Flavor Chemistry and Technology*. 2nd ed. Boca Raton: CRC Press; 2005. DOI: 10.1201/9780203485347
- [32] Djohan YA, Meenune M. Effect of heating conditions on physical and chemical characteristics of sugar syrup. *Asia-Pacific Journal of Science and Technology*. 2021;**26**(1):1-9
- [33] McRae JM, Ziora ZM, Kassara S, Cooper MA, Smith PA. Ethanol concentration influences the mechanisms of wine tannin interactions with poly (L-proline) in model wine. *Journal of Agricultural and Food Chemistry*. 2015;**63**(17):4345-4352
- [34] Gawel R, Smith PA, Ciceralo S, Keast R. The mouthfeel of white wine. *Critical Reviews in Food Science and Nutrition*. 2018;**58**(17):2939-2956. DOI: 10.1080/10408398.2017.1346584
- [35] Methven L. Techniques in sensory analysis of flavour. In: Parker JK, Elmore JS, Methven L, editors. *Flavour Development, Analysis and Perception in Food and Beverages*. Cambridge: Elsevier Ltd; 2016. pp. 353-368. ISBN: 9780081013823
- [36] Hellekant G. Neuroscience of taste: Unlocking the human taste code. *BMC Neuroscience*. 2024;**25**(1):19. DOI: 10.1186/s12868-024-00847-2
- [37] Provost JJ, Colabroy KL, Kelly BS, Wallert MA. *The Science of Cooking. Understanding the Biology and Chemistry behind Food and Cooking*. 1st ed. Hoboken, New Jersey: John Wiley & Sons; 2016. pp. 55-91
- [38] Lancioni C, Castells C, Candal R, Tascon M. Headspace solid-phase microextraction: Fundamentals and recent advances. *Advances in Sample Preparation*. 2022;**3**:100035. DOI: 10.1016/j.sampre.2022.100035
- [39] Wojnowski W, Majchrzak T, Dymerski T, Gębicki J, Namieśnik J. Dynamic headspace sampling as an initial step for sample preparation in chromatographic analysis. *Journal of AOAC International*. 2017;**100**(6):1599-1606. DOI: 10.5740/jaoacint.17-0206
- [40] Blumberg LM. Theory of gas chromatography. In: Blumberg LM, editor. *Gas Chromatography*. Amsterdam: Elsevier; 2021. pp. 19-150. DOI: 10.1016/B978-0-12-820675-1.00026-5
- [41] Baltussen E, Sandra P, David F, Cramers C. Stir bar sorptive extraction (SBSE), a novel extraction technique for aqueous samples: Theory and principles. *Journal of Microcolumn Separations*. 1999;**11**(10):737-747. DOI: 10.1002/(SICI)1520-667X(1999)11:10<737::AID-MCS7>3.0.CO;2-4
- [42] Wichaphon J, Thongthai C, Assavanig A, Lertsiri S. Volatile aroma components of Thai fish sauce in relation to product categorization. *Flavour and Fragrance Journal*. 2012;**27**:149-156
- [43] Jaeger SR, de Silva HN, Lawless HT. Detection thresholds of 10 odor-active

compounds naturally occurring in food using a replicated forced-choice ascending method of limits. *Journal of Sensory Studies*. 2014;**29**(1):43-55. DOI: 10.1111/joss.12085

[44] Grosch W. Evaluation of the key odorants of foods by dilution experiments, aroma models and omission. *Flavour and Fragrance Journal*. 1994;**9**(4):147-152. DOI: 10.1002/ffj.2730090403

[45] Vlasov YU, Legin A, Rudnitskaya A, Di Natale C, D'Amico A. Nonspecific sensor arrays ("electronic tongue") for chemical analysis of liquids (IUPAC technical report). *Pure and Applied Chemistry*. 2005;**77**(11):1965-1983. DOI: 10.1351/pac200577111965

[46] Rudnitskaya A, Lvova L. Chapter 32 gustatory-based electronic tongues. In: Haick H, editor. *Nature-Inspired Sensors*. Amsterdam: Elsevier; 2025. pp. 467-486. DOI: 10.1016/B978-0-443-15684-7.00037-3

[47] Pereira TS, Facure MHM, Mercante LA, de Souza MHG, Braunger ML, Riul A Jr, et al. Chapter 31 electronic tongues: Basics, materials, and applications. In: Haick H, editor. *Nature-Inspired Sensors*. Amsterdam: Elsevier; 2025. pp. 451-466. DOI: 10.1016/B978-0-443-15684-7.00036-1

[48] Lu L, Hu Z, Hu X. Electronic tongue and electronic nose for food quality and safety. *Food Research International*. 2022;**162**:112214. DOI: 10.1016/j.foodres.2022.112214

Sensory Analysis Methods and Quality Characteristics of Foods

Gulcan Koyuncu

Abstract

Sensory evaluation is a discipline that encompasses a wide range of tests to determine the responses of panelists. Sensory analysis is used to determine consumer product preferences in various industries based on sensory attributes, such as taste, odor, texture, and appearance. One of the areas where sensory analysis is most frequently used is the food industry. In sensory analysis, information about the quality characteristics of food is obtained by using the sensory organs of the eye, ear, skin, nose, and tongue. The sensory properties of foods also determine food quality. Because it affects the overall quality of the product, the sensory quality of food items has been regarded as a crucial component from the start of the food industrialization process. Sensory analysis investigates how food is perceived by the consumer beyond its physicochemical properties. It is frequently applied in the stages of the product development process, in consumer research to evaluate product acceptability, and in quality control. In addition to traditional sensory analysis methods, sensory evaluation has made significant progress, thanks to new techniques (biometric measurements, artificial sensory organs, artificial intelligence applications, etc.) used recently. This section will provide an overview of sensory analysis, its definition, history, significance to the food business, fundamental techniques, and sensory quality attributes. Additionally, both traditional and innovative sensory analysis methods will be described. This chapter provides a basic overview of sensory analysis in foods and emphasizes the importance of sensory evaluation.

Keywords: sensory evaluation, food quality, appearance, odor, taste, texture

1. Introduction

Sensory evaluation is a crucial aspect of food science and is often utilized in both industrial applications and research settings. Sensory analysis is a scientific method used to measure, analyze, and interpret reactions to products using the senses of sight, smell, taste, touch, and hearing [1, 2]. As a result, sensory organs serve as detectors that assist the brain in receiving information about food properties from outside stimuli. The characteristics that distinguish one product from another are appearance, taste, smell, texture, and sound [3]. Sensory analysis has made significant progress over the last 15–20 years, thanks to advances and new methods. Sensory evaluation utilizes both human senses and the principles of statistical analysis [4]. Sensory analysis and sensory evaluation do not have the same meaning because

sensory evaluation is a process that involves all five senses [5]. Although sensory evaluation is primarily applied to foods and beverages, it is also used in personal care products, pet food, and many other products [6].

Sensory evaluation bridges the gap between product attributes and consumer expectations and provides a greater understanding of how sensory attributes influence consumer acceptance and purchase decisions [7, 8]. Sensory properties are also an important tool in determining the quality of food [9, 10]. Consumer acceptance of a food depends on its sensory character [11]. No matter how nutritious the food is, if it is not sensory appealing, it is not preferred by consumers [12]. Sensory evaluation is of vital importance in the food industry [13]. Sensory analysis provides successful results in terms of consumer acceptance of the product [11]. When individuals choose a product, they are affected by many factors, such as physiological, sociocultural, and psychological aspects. Sensory factors play a major role in consumers' food preference and purchasing stages [14]. Sensory analysis can also be called organoleptic evaluation, taste test, degustation, sensory evaluation, sensory examination, panel test, and subjective test [15].

The scientific method of measuring and analyzing people's sensory responses to food and drinks is called sensory evaluation [13, 16, 17]. Sensory evaluation techniques are preferred in quality controls, marketing studies, and engineering processes [18]. Sensory analysis studies are carried out following tasting panel protocols [19]. Effective sensory evaluation requires trained panelists, meticulously prepared protocols, and statistical analysis [20]. The evaluations can be performed by trained or untrained panelists. Although trained panelists are not considered machines, they are an important tool in obtaining an accurate sensory result [21, 22]. In sensory analysis, human perceptions are subjective and the evaluations made by the panelists are not definitive [18]. The main purpose of sensory analysis is to conduct valid and reliable tests that enable sound decisions to be made [22]. The steps followed in sensory analysis are used for: determining the purpose, choosing the test method, selecting the panelist, planning the analysis, conducting the analysis, analyzing the data, interpreting, and reporting the analysis results [23]. Reliable sensory evaluation relies on the panelist's ability to optimize four factors: problem definition, test design, instrumentation, and interpretation of results [24]. In many foods, sensory properties deteriorate before reaching microbiological quality, so sensory analysis should be used to monitor changes in the product alongside all other analyses throughout the supply chain [25].

Sensory evaluation has many purposes. Some of them are given as follows:

- a. New product development studies
- b. Cost reduction studies
- c. Quality improvement
- d. Evaluation of product acceptance
- e. Quality control and assurance
- f. Determination of ingredient/process changes [26]
- g. Checking whether the final product meets the original product requirements [4]

h. Process control

i. Decision-making tool in production [5].

One of the prerequisites for successful results in sensory analysis is the selection of the right panelist. There are certain characteristics that panelists must have. These are mentioned as: successfully completing the taste and smell sensitivity test, having enough time for the panel, being eager to take part in the test, not being overly introverted or extroverted, not smoking, not using dentures, not having an allergy to the test food, being in good physical and mental health, not having a prejudice or excessive sympathy for the test food, having verbal expression skills in describing and defining the properties of food, being able to receive training for descriptive analyses, being able to generate terms for descriptive analyses, maintaining communication and objectivity among panelists, not being color blind, giving full concentration to the panel, being free from commercial interests that may affect the test results, being able to work with the reference material given for taste and smell, being prone to teamwork if necessary for the test, and not being overly hungry or overly full [15, 17].

Unlike instrumental methods (gas chromatography, high-performance liquid chromatography, spectrophotometry, etc.) that measure one parameter of the food at a time, sensory evaluation allows the measurement of food quality as a whole [27, 28]. Although it is possible to detect parameters such as odor instrumentally, these devices cannot completely replace panelists [29]. More accurate results can be obtained if relationships are established between instrumental analyses and sensory properties [30]. Chemometric methods can also be used to correlate the results of these methods. With the development of technology, devices such as electronic tongues (e-tongues) and electronic noses (e-noses) have been applied to sensory analysis [12, 28]. Electronic noses use sensors to detect and identify volatile compounds responsible for aroma, while electronic tongues measure taste attributes by detecting ion concentrations in food samples. These methods complement subjective sensory assessments and provide objective data [31]. Recent studies help to correlate sensory analysis data with instrumental measurements [32]. Sensory analysis applied for quality control purposes is focused on three different main areas that include: Ensuring product quality with sensory evaluation studies applied together with instrumental analysis; making sensory analysis mandatory in food quality certification applications; and modeling the parameters and standards that cause quality differences in products [33]. In this section, the history of sensory analysis, the most preferred sensory traditional and innovative test types, human senses, and sensory quality criteria of foods are examined.

2. History of sensory analysis

For centuries, individuals have relied on their senses to assess food. In early applications, sensory analysis was called by general names, such as “food acceptance” or “food preferences.” The definition of sensory analysis was first expressed in 1961 [23]. The first reports of sensory perception date back to the Ancient Greeks, when Aristotle described the five senses in 350 BC [34]. With the advent of trade, standard product quality assessment procedures were established, and these procedures formed the basis of modern sensory analysis [35, 36]. Sensory analysis of foods is a relatively new technique, originating around 1940 with the work of the U.S. Army to

support food acceptance research for the armed forces. By the 1950s, sensory analysis techniques began to be standardized. Over the last two decades, sensory analysis has become a science [10, 22]. Today, sensory analysis is a well-known discipline that appeals to a wide audience and is developing every day [23]. Over the years, researchers in the food field have accepted the use of various methods to measure sensory and hedonic responses [37]. There are differences in application among the various scales. The chronological order of development in the sensory analysis discipline is given below.

1947 The triangle difference test approach was presented.

1948 A ranking test was implemented.

1949 Hedonic scale was created by the Quartermaster Laboratory of the U.S. Army.

1957 The initial book on the fundamentals of sensory analysis was released by Tilgner.

1957 Descriptive analysis of flavor profiles was presented by the Arthur D. Little Company.

1962 The second book on sensory analysis was released by Masuyama and Miura.

1963 The texture profile approach and the odor activity value were presented.

1965 The third book on sensory analysis, authored by Amerine, Pangborn, and Roessler, was released.

1967 A theory for identifying and quantifying sweet taste was suggested.

1968 The American Society for Testing and Materials released its initial handbook on sensory analysis.

1973 Sensory Evaluation unit of the Institute of Food Technology established.

1974 Tragon created quantitative descriptive analysis.

1977 The International Organization for Standardization published sensory analysis guidelines for certain foods.

1989 The European Sensory Network was established [10, 17, 36, 38, 39].

3. Human senses and sensory quality characteristics of food

In sensory analysis, our sensory organs interact with the stimuli around us and perceive the properties of the products [25]. The sensory properties of foods are perceived through five senses: sight, smell, taste, hearing, and touch [24, 40]. The sensory qualities of foods are determined by the use of one or more sense organs. The sensory quality attributes perceived by these organs have a strong influence on purchasing decision [11]. Food characteristics perceived by humans through their sensory organs are given in **Table 1**.

Sense Organ	Perceived Feature
Eye	Color, surface, shape
Nose	Odor, taste
Tongue	Surface, taste, elasticity, hardness, roughness, crispness
Touch	Surface, shape, flexibility, hardness, roughness, crispness
Ear	Crispness

Table 1.
Food characteristics perceived by human senses [41].

3.1 Vision/appearance

The ability of the eye and brain to perceive electromagnetic waves in the visible light range and interpret the image is called vision [25]. The first sense organ used when evaluating the quality and properties of foods is the eyes [39]. Vision is also linked to other senses. The visual appearance of food also affects the identification and intensity of smell and taste. Color is used to assess the preference and acceptability of a food [24]. The visual aspect is the primary criterion utilized to evaluate the quality of food and its alignment with consumer expectations. The appearance of food is evaluated in terms of features, such as shape, color, size, and surface texture. Sensory quality attributes of foods are shown in **Figure 1**.

3.2 Hearing/sound

Sound is a stimulant for the auditory system. The tiny hair cells in the ear are activated by the vibrations in the air caused by sound waves, allowing us to perceive the sound. The sound produced by the food while it is being consumed also contributes to the perception of the texture of the food (e.g., the crunching of an apple while being consumed) [24, 25]. The evaluation is based on the noises produced while cooking and eating food. The sounds associated with a product can influence the consumer's experience in either a favorable or an unfavorable manner. Crispy products make more noise, while soft foods make less noise.

3.3 Touch/texture

The sense of touch is realized by perceiving external factors with the help of receptors located in the skin, muscles, tendons, joints, mucous membranes, and lips [24]. The sense of texture is quite complex and its qualities can be divided into three: mechanical (chewiness, hardness), geometric (granularity, friability), and mouthfeel (moistness, oiliness) [25]. The texture of food products stems from their mechanical, structural, and surface characteristics. The texture of foods is perceived through touch, sight, and sound.

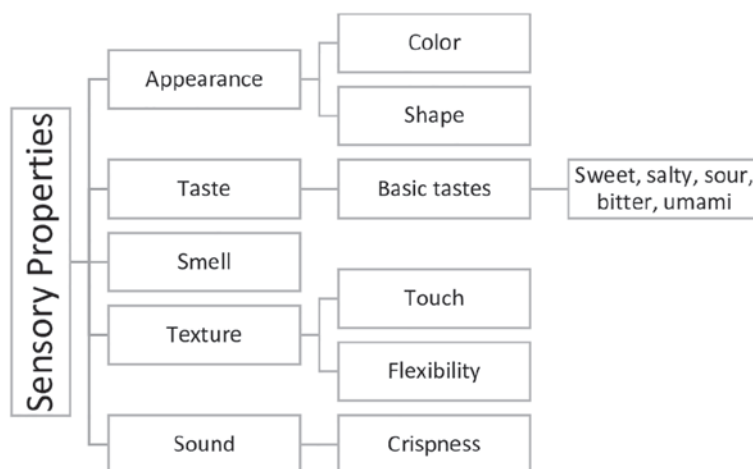


Figure 1.
 Sensory quality characteristics of foods [41].

3.4 Olfactory/odor

Humans have 10–20 million olfactory neurons and epithelium. The odor is dissolved in the mucus and volatile compounds bind to olfactory receptors. Volatile compounds can enter the nose orthonasally through the nose during sniffing and breathing, or retronasally through the back of the throat during eating [42]. Approximately 17,000 distinct volatile compounds have been identified, and a skilled panel of descriptors can typically recognize and label several thousand different scents. Additionally, experienced tasters or perfumers can identify thousands more. These compounds are responsible for the formation of particular odors (e.g., isoamyl acetate—banana odor) [25]. The aroma of food is experienced at the conclusion of a process where volatile compounds present in food travel through the nasal cavity and are detected. The smell determines the aroma of the food and a pleasant aroma makes the food appetizing. The amount of volatile matter sensed from a product is affected by the temperature and the nature of the compound [39]. Volatile compounds are also affected by the condition of a surface; at a given temperature, more volatiles escape from a hard, smooth, dry surface than from a soft, porous, moist surface [43].

3.5 Taste perception/taste

The perception of taste occurs when hydrophilic molecules dissolved in saliva interact with receptors located in the mouth. Taste cells are located in taste buds located both on the surface of the tongue and partially in the epithelium of the palate [44]. Each taste bud contains up to 100 taste cells. There are five fundamental tastes that can be identified. These include salty, sweet, sour, bitter, and umami [45]. It was previously thought that the basic taste receptors were located in a specific part of the tongue (tip-sweet, front side-salty, back side-sour, root-bitter). It is now commonly believed that taste receptors are uniformly spread across the tongue's surface. Salty taste is produced by sodium chloride and potassium chloride; sweet taste is produced by sucrose, glucose, and aspartame; sour taste is produced by citric acid and phosphoric acid; bitter taste is produced by quinine; and caffeine and umami taste is produced by monosodium glutamate [25].

3.6 Multimodal perception/flavor

The stimuli from each sensory organ are combined in the brain. For example, the perception of taste is the combination of perceptions obtained from all sensory organs [25]. Flavor encompasses the overall experience of taste, aroma, and mouthfeel. Mouthfeel refers to the sensations produced by a specific food in the mouth. Aroma has a strong influence on flavor and accounts for 75% of the flavor impression [24]. Flavor release does not occur all at once, nor does it occur at a constant rate [46]. Consumers often form opinions about food by combining perceptions from all of their senses. Words frequently used to describe basic sensory quality attributes of foods are given in **Table 2**.

3.7 Flaw

One of the features that significantly affects quality in the eyes of the consumer is defect. The absence of the necessary qualities for a product or the presence of some elements that negatively affect quality is defined as deviation from perfection.

Sensory Feature	Word Bank
Appearance	Delicious, appealing, fragile, charred, porous, transparent, murky, chilly, vibrant, colorless, rich, flaky, crystalline, deep, arid, frothy, new, textured, oily, nutritious, damp, spotted, non-transparent, light, dusty, glossy, slippery, sleek, soggy, tacky, stringy, dense, see-through, liquidy.
Taste	Sour, bitter, flavorless, charred, rich, refreshing, smooth, greasy, aromatic, heated, moldy, zesty, indulgent, savory, pungent, smoky, acidic, fiery, old, sugary, piquant, tangy, flavorful, bland, poorly cooked, diluted, lively.
Smell	Acrid, scented, sharp, charred, java, aged, blooming, fragrant, invigorating, tangy, herbal, green, damp, intense, foul, cooked, decayed, perfumed, charred, acidic, zesty, stale.
Texture	Adhesive, light, fragile, frothy, chewy, rough, sticky, chilly, crunchy, brittle, crisp, clear, arid, bubbly, flexible, stringy, delicate, solid, carbonated, flaky, flat, airy, granular, oily, coarse, tough, succulent, uneven, damp, soft, squishy, powdery, elastic, sandy, slippery, sleek, gentle, cushiony, tender.
Sound	Bubbling, crackling, crunchy, grating, fizzy, searing, sizzling, snapping.

Table 2.
Words describing food quality characteristics [40, 47].

Deviation from perfection in food can be defined as foreign substances, changes that may occur during processing, transportation, and storage, tissue disorders, formation of lines and spots, and the absence of one of the necessary elements [15].

4. Traditional sensory analysis methods

Sensory evaluation techniques are essential tools used across industries to understand consumers' product preferences and perceptions based on sensory attributes, such as taste, aroma, appearance, and texture [47]. Most sensory tests are simple and easy to perform. Other methods are more complex and require training and experience. Selecting the appropriate sensory test and testing conditions will help to achieve accurate results [19]. There are many test methods determined according to the purposes of sensory analysis [48]. Every testing approach has its unique advantages and disadvantages. Choosing the most appropriate test method is of great importance to achieve accurate results [49]. These tests are divided into three main categories: discriminative, descriptive, and affective tests [40, 50].

Discrimination tests are used to determine whether samples are different from each other [36, 42]. These tests are also suitable for determining changes to be made in food formulation or processing [5]. Frequently preferred discrimination test methods are sequential, paired difference, A and non-A, duo-trio, napping, tetrad, and triangle [39, 51–53]. In discriminatory methods, no training is required for panelists. The number of panelists varies depending on the differences between products and the level of acceptable statistical risk [54]. Discrimination tests are usually small panels conducted with 12–20 panelists. These tests can be conducted with 24–50 panelists and may not be repeated [49]. These tests are used in case of alternative suppliers or process changes in accordance with specific research objectives [55]. In napping, untrained participants evaluate products based on their similarities and differences. This allows all samples to be compared. It is not suitable for analyses requiring pre-prepared samples [56]. The type of discriminant test is selected based

on the food type and is applied based on various parameters, such as the replacement of an ingredient in the product, new equipment design, or deviations from established protocols during production [57]. The triangular test is a popular discriminant test. In this test, three samples are presented simultaneously, two identical and one different, and panelists are asked to identify the sample that is different [34]. In tetrad tests, four samples are presented, two from the first group and two from the second group [57]. They are very useful for panelists to identify changes in food production processes and ingredients. Paired and triplicate tests are alternatives to the triangular test. Panelists are presented with three samples, one of which is a reference, and they can identify the sample closest to the reference. The A-Not A test is another discriminatory method that requires the evaluator to present reference A and other samples and then decide whether the other evaluated samples are similar to sample A [34].

Descriptive tests are used to describe the sensory properties of products and measure the intensity of these properties [23]. In descriptive analysis, the properties of a food are revealed by quantitative methods [5]. It is usually performed with 6–12 panelists [49]. This method is also known as trained panel profiling [36]. The most commonly applied descriptive analyses are texture profile, quantitative descriptive analysis, free choice profiling, flash descriptive analysis, spectrum, check-all-that-apply, napping, and flash profile. In check-all-that-apply, known as CATA, panelists express their opinions about a product through a multiple-choice questionnaire without any restrictions. Flash profiling, on the other hand, is a two-step evaluation technique. In the first step, descriptive terms are developed, and in the second, products are ranked from low to high or high to low using these terms [56]. Descriptive analysis is crucial for developing optimal products as it focuses on identifying the sensory drivers of foods [34].

Acceptance-preference tests are used to determine the likability, acceptability, and preferability of a product over another [47]. The hedonic method most commonly utilized by consumers is part of the acceptance test group. For an accurate evaluation of 2–4 different samples, 80–100 consumers are recommended [42]. Hedonic methods are characterized by their ability to measure consumers' subjective individual responses regarding their preference, acceptance, liking, or perception of a product's benefits [34]. Polarized sensory positioning analysis is also used in preference testing. In this analysis, reference samples are used to identify product differences and similarities. These references must not only be different from the product being analyzed but must also demonstrate the product's essential characteristics [56].

5. Innovative approaches to sensory evaluation

Sensory analysis is constantly evolving with new applications and techniques. Recently, innovative approaches to sensory assessment have been used, such as measuring biometric responses or using artificial senses [58]. Using these innovative techniques can save time and money, increase efficiency, complement traditional methods, and more clearly define consumer preferences. Results can be quantified and standardized, ensuring repeatability. It eliminates the need for trained panelists, thus reducing costs. It also has a wider measurement range than humans [50, 58, 59]. Modern techniques used in sensory evaluation have become an alternative for obtaining fast and reliable results in the food industry [58].

Human reactions are divided into conscious and subconscious reactions.

Facial expressions: People can subconsciously reveal their emotions through facial

movements. Various software programs have been developed with algorithms that can detect and measure facial movements and translate these signals into emotional responses. Generally, the results show that these measurements are more sensitive for negative emotions. Other biometric techniques, such as heart rate, body temperature, and skin conductance, can also be used to measure the emotional state of participants or panels in response to different stimuli. Decreases in body temperature and increases in heart rate and skin conductance can also be indicators of fear-related emotions. Eye tracking is a new biometric technique used to measure participants' physical gaze input to visual stimuli. This process utilizes eye-tracking devices that capture retinal movements [50].

The use of technology in sensory assessment allows us to more reliably determine the sensory properties of foods by simulating the functioning of the five senses. These include electronic noses and electronic tongues that react chemically upon contact with food; image analysis using devices like cameras that simulate vision; and technological devices that measure force and sound by simulating touch and hearing. Volatile organic compounds, which make up the odor of food, can be quickly and reliably determined with electronic noses. Thanks to their electrochemical sensors, electronic noses can distinguish, identify, and group volatile compounds [58]. Tasting results are highly subjective, and repeatability and remeasurement of these results are made possible with e-tongue applications. While the human tongue can only identify five basic tastes, the e-tongue can also detect other tastes, such as oily and metallic. E-tongue applications can also be used to determine the origin of food or detect counterfeit foods [50]. Colorimeters or artificial vision systems can be used to mimic the visual sense. Colorimeters are sensor devices that determine the color of food. They analyze light reflections on the surfaces of objects to determine color tones. The device provides a representative code for the identified tone. Machine vision systems, also known as computer vision systems, provide information about the color, shape, size, and other characteristics of food [60]. These systems have become an alternative for eliminating human errors in quality control. Texture analyzers or texture meters are used to measure food texture. These devices simulate jaw biting and chewing movements and generate electrical signals for a computer when the device comes into contact with the food. By analyzing these signals, product properties, such as hardness, brittleness, chewiness, elasticity, and stickiness, can be determined [61].

New methods mentioned in sensory studies have only been used in recent years. However, initial findings suggest that new techniques can be combined with traditional sensory assessments to provide more information about participants' responses to stimuli [50].

6. Relationship between sensory properties of foods and quality

Determining the sensory difference between foods is important not only for gaining consumer preference but also for revealing food quality [62]. While objective analyses focus on measuring a feature of the food, sensory analysis determines the overall quality with the response to stimuli resulting from consumption [63, 64]. Sensory analyses are used as a technical support for the quality assurance of foods [63]. Food quality is created by internal and external factors. Examples of internal factors include color, size, appearance, texture, and shape; and external factors include packaging, price, and convenience [65]. While internal factors generally determine purchasing choice, external factors provide continuity in product selection. Internal

and external factors are effective together in purchasing products [62]. The quality of foods is determined by sensory properties as well as physical structure, chemical properties, and contaminants [63]. Sensory quality is very important and varies not only depending on the characteristics of the food but also on the interaction between the consumer and the food. Sensory analysis is a relatively new application compared to other physical, chemical, and microbiological analysis methods [64].

The quality of food can be measured by the level at which a food meets the expectations and needs of the consumer. Sensory analysis creates a quality perception for food [66]. The biggest factor that determines food selection worldwide is the sensory qualities of food. No matter how developed analytical methods are, they cannot determine the qualities determined by human sensory perception [67]. In addition to objective methods, sensory analyses are indispensable applications both in new product development and in the control of existing products [63]. Standard quality and sensory properties are needed for repeat purchases in foods [68]. If sensory analyses are applied correctly, they help the manufacturer reduce or completely prevent unwanted errors [63]. In addition to the classical sensory evaluation focusing on product quality, there have been recent studies that try to understand the consumer better by using neuroscientific methods in sensory analysis [69].

7. Conclusion and recommendations

The necessity of determining food quality characteristics for consumer acceptance and market share reveals the importance of sensory evaluation. Sensory analysis is a decision aid at all stages of development and is essential for innovation and marketing. From appearance to sound, from taste balance to aroma, every element influences the consumer decision. The choice of sampling method is essential to represent the use of the products and to ensure good reproducibility of the tests. The choice of sensory analysis is also essential and depends on the objectives. These sensory tools can guarantee that the outcomes of the studies are relevant to the end user and that the product meets the sensory preferences of the target consumer. Assessing food through sensory evaluation is a highly intricate and specialized field. It is important to note that no technological apparatus can rival the human senses of taste, smell, touch, and sight when it comes to detecting the nuanced variations in food aroma, flavor, texture, and visual appeal. In both laboratories and food production facilities, it is advisable for sensory evaluation to be conducted alongside instrumental analysis. The palatability of the product is the most important factor in individuals' food preferences. In this section, the definition of sensory analysis, its historical development, basic quality criteria, methods used, and application areas are explained, creating a comprehensive foundation for the subject. Basing sensory analysis processes on scientific, systematic, and ethical foundations stands out as one of the fundamental elements that directly affect product success. The way we perceive the taste, aroma, and texture of foods plays a significant role in shaping our food preferences and eating behaviors. With advancements in technology and changing consumer expectations, sensory evaluation will remain an essential part of creating successful food products. Sensory science will continue to evolve by integrating new techniques to achieve a holistic understanding of human perception. The use of new techniques in sensory evaluation holds promise for food science. However, their full adoption will be gradual. New technologies and methodologies used alongside traditional methods should be controlled by reducing objectivity and used holistically for the most accurate results.

Author details

Gulcan Koyuncu
Technical Sciences Vocational School, Department of Food Processing, Kilis 7 Aralik
University, Kilis, Turkey

*Address all correspondence to: gulcan.koyuncu@kilis.edu.tr

IntechOpen

© 2025 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. 

References

- [1] Pop MD. Sensory evaluation techniques of food. The Annals of “Valahia” University of Targoviste. 2023;**15**(2):58-62. DOI: 10.2478/agr-2023-0019
- [2] Ruiz-Capillas C, Herrero AM. Sensory analysis and consumer research in new product development. Food. 2021;**10**:582. DOI: 10.3390/foods10030582
- [3] Murray JM, Delahunty CM, Baxter IA. Descriptive sensory analysis: Past, present and future. Food Research International. 2001;**34**:461-471. DOI: 10.1016/S0963-9969(01)00070-9
- [4] Padmavathi D. A general review on recent trends in “food sensory science”. International Journal of Research. 2018;**5**(19):724-731
- [5] Agriculture Institute. Quality Attributes of Food: Understanding Sensory and Chemical Properties [Internet]. 2023. Available from: <https://agriculture.institute/food-fundamentals-cpo/quality-attributes-of-food-sensory-chemical-properties/>
- [6] Prinyawiwatkul W, Tepper BJ, Hartel R. Advances in sensory science: From perception to consumer acceptance. Journal of Food Science. 2023;**202388**:A2-A4. DOI: 10.1111/1750-3841.16540
- [7] Lönnerdal B. Genetically modified plants for improved trace element nutrition. The Journal of Nutrition. 2003;**133**(5):1490S-1493S. DOI: 10.1093/jn/133.5.1490S
- [8] Abbas M. Sensory evaluation techniques: Understanding consumer preferences. Journal of Food Science and Nutrition. 2024;**7**(3):238. DOI: 10.35841/aajfsn-7.3.238
- [9] Gamis JG, Jesus GF, Pinas RB Jr, Labalan JD, Espedido RK. Sensory evaluation of the developed product. International Journal of Innovative Science and Research Technology. 2022;**7**(11):1459-1463. DOI: 10.5281/zenodo.7463551
- [10] Schiano AN, Harwood WS, Drake MA. A 100-year review: Sensory analysis of milk. Journal of Dairy Science. 2017;**100**:9966-9986. DOI: 10.3168/jds.2017-13031
- [11] Priulli E, Pereira CMT, Oliveira AC, Pires CRF. Use of the quantitative descriptive analysis for sensory assessment of tapiocas with adding waste from soy processing. Food Science and Technology. 2022;**42**:e08621. DOI: 10.1590/fst.08621
- [12] Sirangelo TM. Sensory descriptive evaluation of food products: A review. Journal of Food Science and Nutrition Research. 2019;**2**(4):354-363. DOI: 10.26502/jfsnr.2642-11000034
- [13] Rodrigues SSQ, Dias LG, Teixeira A. Emerging methods for the evaluation of sensory quality of food: Technology at service. Current Food Science and Technology Reports. 2024;**2**:77-90. DOI: 10.1007/s43555-024-00019-7
- [14] Karaman EE, Çetinkaya N. Gıda tercihinde duyuların rolü: Tat duyusunun tat testi ile demografik özelliklere göre farklılığının tespiti. Atatürk Üniversitesi Sosyal Bilimler Enstitüsü Dergisi. 2020;**24**(2):883-898
- [15] Altuğ Onoğur T, Elmacı Y. Gıdalarda Duyusal Değerlendirme. 1st ed. İzmir: Sidas Medya; 2015. 134 p
- [16] Green R, Allen LH, Bjorke-Monsen AL, Brito A, Gueant JL,

- Miller JW, et al. Vitamin B12 deficiency. *Nature Reviews Disease Primers*. 2017;3:17054. DOI: 10.1038/nrdp.201754
- [17] Stone H, Sidel JL. *Sensory Evaluation Practices*. 2nd ed. California: Academic Press; 1993. 338 p. DOI: 10.1016/C2009-0-03318-2
- [18] Martinez L. Sensory evaluation based on linguistic decision analysis. *International Journal of Approximate Reasoning*. 2007;44(2):148-164. DOI: 10.1016/j.ijar.2006.07.006
- [19] Drake MA. Invited review: Sensory analysis of dairy foods. *Journal of Dairy Science*. 2007;90:4925-4937. DOI: 10.3168/jds.2007-0332
- [20] Kibirige D, Mwebaze R. Vitamin B12 deficiency among patients with diabetes mellitus: Is routine screening and supplementation justified? *Journal of Diabetes & Metabolic Disorders*. 2013;12:1-6. DOI: 10.1186/2251-6581-12-17
- [21] Meiselman H. The future in sensory/consumer research: Evolving to a better science. *Food Quality and Preference*. 2013;27:208-214. DOI: 10.1016/j.foodqual.2012.03.002
- [22] Pinto MM. Evaluating uncertainty in sensory analysis. A case study of the panel of tasters of the Dão regional wine commission. *Ciencia e Tecnica Vitivinicola*. 2021;36(1):22-31. DOI: 10.1051/ctv/ctv2021360122
- [23] Mahieu B. *Sensory Analysis with Consumers Using Free-Comment: Analyses, Performances and Extensions. Other Statistics*: Université Bourgogne Franche-Comté; 2021. English
- [24] Choi SE. Sensory evaluation. In: Edelman S, editor. *Food Science: An Ecological Approach*. 1st ed. Burlington, Massachusetts: Jones and Bartlett Learning LLC; 2013. pp. 83-111
- [25] Kemp SE, Hollowood T, Hort J. *Sensory Evaluation: A Practical Handbook*. 1st ed. Chichester, West Sussex: John Wiley & Sons; 2009. 196 p. DOI: 10.1002/9781118688076
- [26] Carbonell-Barrachina AA. Application of sensory evaluation of food to quality control in the Spanish food industry. *Polish Journal of Food and Nutrition Sciences*. 2007;57(4):71-76
- [27] Cordero C, Bicchi C, Rubiolo P. Group-type and fingerprint analysis of roasted food matrices (coffee and hazelnut samples) by comprehensive two-dimensional gas chromatography. *Journal of Agricultural and Food Chemistry*. 2008;56(17):7655-7666. DOI: 10.1021/jf801001z
- [28] Huang K. The development of sensory analysis techniques in the food industry and the research progress. *Theoretical and Natural Science*. 2024;71(1):164-169. DOI: 10.54254/2753-8818/2024.la18891
- [29] Bower JA. Statistics for food science III: Sensory evaluation data. Part A– Sensory data types and significance testing. *Nutrition & Food Science*. 1995;6:35-42. DOI: 10.1108/00346659510103647
- [30] Wright JM, Carunchia Whetstone ME, Miracle RE, Drake MA. Characterization of a cabbage off-flavor in whey protein isolate. *Journal of Food Science*. 2006;71:C91-C96. DOI: 10.1111/j.1365-2621.2006.tb08887.x
- [31] Van Horn L. Advances in food sensory evaluation: Techniques and technologies for assessing consumer preferences. *Journal of Food Science and*

Nutrition. 2024;7(4):249. DOI: 10.35841/aajfsn-7.4.249

[32] Kilcast D. Combining instrumental and sensory methods in food quality control. In: Kilcast D, editor. *Sensory Analysis for Food and Beverage Quality Control - A Practical Guide*. 1st ed. Sawston, Cambridge: Woodhead Publishing; 2010. pp. 97-117. DOI: 10.1533/9781845699512.2.97

[33] Nguyen DQ, Le TM, Nguyen DH. Role of sensory evaluation in quality control: A textual point of view. In: *From Senses to Quality: What Can Sensory Evaluation Bring to Quality Control*; 25-27 July 2014; Vietnam. 2014. pp. 55-60

[34] Marques C, Correia E, Dinis LT, Vilela A. An overview of sensory characterization techniques: From classical descriptive analysis to the emergence of novel profiling methods. *Food*. 2022;11:255. DOI: 10.3390/foods11030255

[35] Drake MA, Drake S, Bodyfelt F, Clark S, Costello M. History of sensory analysis. In: Clark S, Costello M, Drake M, Bodyfelt F, editors. *The Sensory Evaluation of Dairy Products*. 1st ed. New York: Springer; 2008. pp. 1-6

[36] Drake MA, Watson ME, Liu Y. Sensory analysis and consumer preference: Best practices. *Annual Review of Food Science and Technology*. 2023;14:427-448. DOI: 10.1146/annurev-food-060721-023619

[37] Pimentel TC, Gomes da Cruz A, Deliza R. Sensory evaluation: Sensory rating and scoring methods. In: Caballero B, Finglas PM, Toldra F, editors. *Encyclopedia of Food and Health*. 1st ed. Cambridge: Academic Press; 2015. pp. 744-747. DOI: 10.1016/B978-0-12-384947-2.00617-6

[38] Munekata PES, Pateiro M, Dominguez R, Sepulveda N, Santos EM, Lorenzo JM. Historical perspective of sensory analysis for the development of meat products: A contemporary challenge. In: Lorenzo JM, Pateiro M, Saldana E, Munekata PES, editors. *Sensory Analysis for the Development of Meat Products- Methodological Aspects and Practical Applications*. 1st ed. UK: Woodhead Publishing; 2022. pp. 1-27. DOI: 10.1016/C2019-0-05236-3

[39] Meilgaard MM, Civille GV, Carr BT. *Sensory Evaluation Techniques*. 5th ed. Boca Raton, FL: CRC Press; 2016. 630 p. DOI: 10.1201/b19493

[40] PDST. Sensory analysis Teacher's manual. In: Home Economics Support Service 2004. Dublin; 2017

[41] Balazs SP. Sensory evaluation in food industry [Internet]. Szegedi Tudományegyetem; 2012. Available from: https://eta.bibl.uszeged.hu/731/1/sensory_evaluation_in_food_teljes.pdf. [Accessed: May 14, 2025]

[42] Lawless HT, Heymann H. *Sensory Evaluation of Food: Principles and Practices*. 2nd ed. New York: Springer; 2010. 471 p. DOI: 10.1007/978-1-4419-6488-5

[43] Laing DG. Natural sniffing gives optimum odour perception for humans. *Perception*. 1983;12(2):99-117. DOI: 10.1068/p120099

[44] Brown A. *Understanding Food: Principles and Preparation*. 3rd ed. Belmont, CA: Thompson-Wadsworth; 2008. p. 704

[45] Delgado A, Al-Hamimi S, Ramadan MF, Wit MD, Durazzo A, Nyam KL, et al. Contribution of tocopherols to food sensorial properties, stability, and overall quality. *Journal of Food*

Quality. 2020;**2020**:8885865. DOI: 10.1155/2020/8885865

[46] Keefer HRM, Rovai D, Drake M. A timely application-temporal methods, past, present, and future. *Journal of Food Science*. 2023;**88**(S1):21-52. DOI: 10.1111/1750-3841.16491

[47] Singh-Ackbarali D, Maharaj R. Sensory evaluation as a tool in determining acceptability of innovative products developed by undergraduate students in food science and Technology at the University of Trinidad and Tobago. *Journal of Curriculum and Teaching*. 2014;**3**(1):10-27. DOI: 10.5430/jct.v3n1p10

[48] Sipos L, Agoston KC, Biro P, Bozoki S, Csato L. How to measure consumer's inconsistency in sensory testing? *Current Research in Food Science*. 2025;**10**:100982. DOI: 10.1016/j.crfs.2025.100982

[49] Sidel JL, Stone H, Bloomquist J. Use and misuse of sensory evaluation in research and quality control. *Journal of Dairy Science*. 1981;**64**(11):2296-2302. DOI: 10.3168/jds.S0022-0302(81)82846-9

[50] Torrico DD, Mehta A, Borssato AB. New methods to assess sensory responses: A brief review of innovative techniques in sensory evaluation. *Current Opinion in Food Science*. 2023;**49**:100978. DOI: 10.1016/j.cofs.2022.100978

[51] Ennis JM, Rousseau B, Ennis D. Sensory difference tests as measurement instruments: A review of recent advances. *Journal of Sensory Studies*. 2014;**29**:89-102. DOI: 10.1111/joss.12086

[52] Garcia K, Ennis JM, Prinyawiwatkul W. A large-scale experimental comparison of the tetrad and triangle tests in children. *Journal of*

Sensory Studies. 2012;**27**:217-222. DOI: 10.1111/j.1745-459X.2012.00385.x

[53] Capriles VD, Valéria de Aguiar E, Garcia Dos Santos F, Fernández MEA, de Melo BG, Tagliapietra BL, et al. Current status and future prospects of sensory and consumer research approaches to gluten-free bakery and pasta products. *Food Research International*. 2023;**173**(Pt. 2):113389. DOI: 10.1016/j.foodres.2023.113389

[54] Rousseau B. Sensory discrimination testing and consumer relevance. *Food Quality and Preference*. 2015;**43**:122-125. DOI: 10.1016/j.foodqual.2015.03.001

[55] Yeh E, Schiano AN, Jo Y, Barbano DM, Drake MA. The effect of vitamin concentrates on the flavor of pasteurized milk. *Journal of Dairy Science*. 2017;**100**:4335-4348. DOI: 10.3168/jds.2017-12613

[56] Ruiz-Capillas C, Herrero AM, Pintado T, Delgado-Pando G. Sensory analysis and consumer research in new meat products development. *Food*. 2021;**10**:429. DOI: 10.3390/foods10020429

[57] Burns SL, Pen MP, Saxton AM, Luckett CR. Comparison of triangle and tetrad discrimination methodology in an applied manner. *Food Quality and Preference*. 2018;**68**:105-112. DOI: 10.1016/j.foodqual.2018.02.009

[58] Martinez-Velasco JD, Filomena-Ambrosio A, Garzón-Castro CL. Technological tools for the measurement of sensory characteristics in food: A review. *F1000 Research*. 2024;**1**(12):340. DOI: 10.12688/f1000research.131914.2

[59] Gonzalez Viejo C, Torrico DD, Fuentes S. Editorial: Advances in sensory evaluation of foods. *Frontiers in Food*

- Science and Technology. 2024;**4**:1534473. DOI: 10.3389/frfst.2024.1534473
- [60] Zhu L, Spachos P, Pensini E, Plataniotis KN. Deep learning and machine vision for food processing: A survey. *Current Research in Food Science*. 2021;**4**:233-249. DOI: 10.1016/j.crfs.2021.03.009
- [61] Nishinari K, Fang Y, Rosenthal A. Human oral processing and texture profile analysis parameters: Bridging the gap between the sensory evaluation and the instrumental measurements. *Journal of Texture Studies*. 2019;**50**(5):369-380. DOI: 10.1111/jtxs.12404
- [62] Lee HS, van Hout D. Quantification of sensory and food quality: The R-index analysis. *Journal of Food Science*. 2009;**74**(6):R57-R64. DOI: 10.1111/j.1750-3841.2009.01204.x
- [63] Mihafu FD, Issa JY, Kamiyango MW. Implication of sensory evaluation and quality assessment in food product development: A review. *Current Research in Nutrition and Food Science*. 2020;**8**(3):690-702. DOI: 10.12944/CRNFSJ.8.3.03
- [64] Costell E. A comparison of sensory methods in quality control. *Food Quality and Preference*. 2002;**13**:341-353. DOI: 10.1016/S0950-3293(02)00020-4
- [65] Jaros D, Rohm H, Strobl M. Appearance properties—A significant contribution to sensory food quality? *LWT - Food Science and Technology*. 2000;**33**(10):320-326. DOI: 10.1006/fstl.2000.0666
- [66] Peri C. The universe of food quality. *Food Quality and Preference*. 2006;**17**(1-2):3-8. DOI: 10.1016/j.foodqual.2005.03.002
- [67] Visalli M, Galmarini MV. Multi-attribute temporal descriptive methods in sensory analysis applied in food science: A systematic scoping review. *Comprehensive Reviews in Food Science and Food Safety*. 2024;**23**(1):e13294. DOI: 10.1111/1541-4337.13294
- [68] Jürkenbeck K, Spiller A. Importance of sensory quality signals in consumers' food choice. *Food Quality and Preference*. 2021;**90**:104155. DOI: 10.1016/j.foodqual.2020.104155
- [69] Adhikari K. Application of selected neuroscientific methods in consumer sensory analysis: A review. *The Journal of Food Science*. 2023;**88**(S1):53-64. DOI: 10.1111/1750-3841.16526

Chapter 6

Rapid Descriptive Methodologies in Food Sensory Analysis: CATA, Free Choice Profile and Flash Profile

Reynaldo Justino Silva-Paz,

Nicodemo Crescencio Jamanca-Gonzales,

Thalia Alexandra Rivera-Ashqui and Amparo Eccoña-Sota

Abstract

This chapter explores rapid descriptive sensory analysis methodologies (Check-All-That-Apply (CATA), Free Choice Profile (FCP), Flash Profile (FP), Pivot Profile, and Napping®) as efficient alternatives to traditional methods. These techniques enable the collection of reliable data using untrained panels or consumers, reducing time and costs in food product development. Their theoretical foundations, practical applications, and limitations are discussed: CATA is notable for its simplicity, using predefined lists of terms; FCP captures individual perceptions through free vocabulary; FP combines direct comparison with spontaneous description; Pivot Profile compares samples to a reference product; and Napping® maps similarities among products in a two-dimensional space. Practical aspects highlight the importance of selecting appropriate participants, designing balanced sessions, and employing specific statistical analyses. A case study with muffins illustrates how these techniques discriminate between formulations with different sugar content: CATA identified key attributes (“sweet” and “moist”), FP detected textural differences, and Napping® confirmed similarity-based groupings. In conclusion, these methodologies offer agility without compromising rigor, making them ideal for the food industry. Their selection depends on the study objectives, product complexity, and available resources. Future research could integrate them with advanced sensometric tools to enhance accuracy and product development.

Keywords: descriptive profile, rapid methods, consumers, food development, muffin

1. Introduction

Sensory evaluation of food is a fundamental scientific discipline for understanding consumer preferences and perceptions, as well as for optimizing food product development [1]. Traditionally, classical descriptive sensory methods, such as

Quantitative Descriptive Analysis (QDA®), require trained panels and considerable time for implementation [2]. However, in recent years, there has been a growing demand for rapid methodologies that provide descriptive information efficiently without compromising data reliability [3]. In this context, techniques like Check-All-That-Apply (CATA), Free Choice Profile (FCP), and Flash Profile (FP) have gained relevance for their flexibility, speed, and adaptability to various research needs [4]. These methodologies are particularly useful in industrial and academic settings where quick feedback is essential for decision-making, such as in the development of new products or food reformulation [5].

Conventional sensory analysis has proven highly effective but can be costly and time-consuming [6]. For example, training a descriptive panel can take weeks or even months, which is not always feasible in industrial settings that require agile responses [7]. Rapid methods have emerged as an alternative to overcome these limitations, enabling the collection of descriptive data using untrained or semi-trained panels [8]. These techniques rely on simplified approaches that prioritize speed while maintaining result validity. Among the most commonly used methodologies are: (i) CATA (Check-All-That-Apply): a multiple-choice method where evaluators select the terms from a predefined list that best describe a product [1]. (ii) Free Choice Profile (FCP): a technique in which each participant generates their own descriptive vocabulary, allowing individualized product characterization [9]. (iii) Flash Profile (FP): a hybrid method that combines ranking and description, where evaluators compare products and generate their own attributes [10]. These methodologies have been widely validated in recent studies, demonstrating their effectiveness in product discrimination and preference identification [11].

The food industry constantly faces challenges such as reducing sugar, sodium, or fat in products without compromising sensory acceptability [12]. In this context, rapid methods offer a competitive advantage by providing immediate feedback on the sensory characteristics of alternative formulations [5]. For example, CATA has been successfully applied in studies on dairy, meat, and snack products, helping identify key attributes that influence consumer preference [7]. FCP has proven useful in evaluating complex products such as wines and cheeses, where consumer perceptions vary significantly [13]. FP has been applied in the comparison of commercial brands and prototypes, standing out for its ability to differentiate products with minor variations [14]. Despite their advantages, these techniques have limitations. For instance, CATA depends heavily on the list of terms provided, which may bias results if not well-designed [11]. In FCP, data analysis can be complex due to the heterogeneity of participant-generated vocabularies [15]. Lastly, FP requires that evaluators be somewhat familiar with the products, which can limit its applicability in some contexts [14]. The aim of this chapter is to compare these three rapid descriptive sensory analysis techniques, discussing their theoretical foundations, practical applications, strengths, and limitations. Recent case studies will also be explored to illustrate their usefulness in the food industry.

2. Rapid descriptive techniques in sensory analysis of foods

Traditional descriptive sensory analysis, such as Quantitative Descriptive Analysis (QDA®), requires trained panels and extended execution time [2]. However, in recent years, rapid descriptive methodologies have gained relevance due to their efficiency, flexibility, and ability to generate reliable data using untrained or semi-trained

consumers [7]. These techniques allow the evaluation of food products in early development stages, optimizing resources and accelerating decision-making in the food industry [3]. Below are the main rapid techniques currently used, including their theoretical foundations, applications, and limitations.

2.1 Free choice profile (FCP)

The Free Choice Profile (FCP), developed by Williams and Langron (1984), is an alternative to conventional profiling, allowing each evaluator to use their own descriptive vocabulary [9]. Unlike traditional methods that use a consensus attribute list, FCP is based on individual perception, making it suitable for use with untrained consumers [16]. FCP has been applied in evaluating complex products such as cheeses, wines, and meats, where sensory differences can be subtle and difficult to describe with standardized language [13]. A recent study applied FCP to characterize artisanal honeys, demonstrating its ability to discriminate between varieties based on spontaneously generated consumer descriptors [17].

2.2 Flash profile (FP)

Developed by Sieffermann (2000), Flash Profile (FP) combines direct product comparison with the generation of attributes by evaluators [10]. Unlike FCP, in FP, participants compare all products simultaneously and generate descriptor lists based on perceived differences [14]. FP has been widely used in the evaluation of dairy, bakery, and beverage products, where small formulation changes can significantly affect sensory perception [18]. A recent study applied FP to compare reduced-sugar jams, identifying key attributes influencing acceptability [19].

2.3 Check-all-that-apply (CATA)

The CATA method involves presenting evaluators with a list of descriptive terms and asking them to mark those they find applicable to the product [1]. It is a quick and simple technique, widely used in consumer studies [4]. CATA has been applied in evaluating snacks, dairy, and meat products, helping identify the most relevant attributes for consumer preference [5]. A recent study used CATA to evaluate vegan ice creams, finding that terms such as “creamy” and “balanced sweetness” were key to consumer acceptance [20].

2.4 Pivot profile (PP)

The Pivot Profile (PP), developed by Thuillier et al. [21], combines free description with a reference product (pivot). Evaluators describe differences between each sample and the pivot, generating a comparative profile [22]. This technique has proven useful in evaluating beers, cheeses, and bakery products, where prototype comparison with a standard is required [23]. A recent study applied PP in the reformulation of whole-grain cookies, identifying sensory changes after fat reduction [24].

2.5 Napping® and projective mapping (PM)

Napping®, developed by Pagès [25], is a projective mapping technique in which evaluators place samples on a two-dimensional space according to perceived

similarity [26]. It is complemented by free description (Napping + Ultra Flash Profile) to obtain qualitative information [14]. Napping® has been used in the evaluation of wines, coffees, and chocolates, where global perception is more relevant than individual attributes [27]. A recent study applied Napping® to specialty coffees, identifying groupings based on roast profiles [28].

3. Practical aspects in the implementation of rapid methods

The successful implementation of rapid sensory techniques requires careful planning in participant selection, experimental design, and data analysis to ensure reliable and applicable results. First, participant selection varies by methodology (**Table 1**): CATA and Napping® can be effectively applied with untrained consumers due to their simplicity, whereas FCP and FP perform better with semi-trained panels or those familiar with the products, as they require spontaneous descriptor generation [7]. In all cases, it is crucial to recruit an adequate number of evaluators (generally 50–100 for CATA and Napping®, and 10–20 for FP and FCP) to ensure statistical robustness [4]. It is also recommended to conduct a brief familiarization session before evaluation, especially for FP and Napping®, where task comprehension is key to avoiding bias [14].

Regarding experimental design, it is essential to control variables that could influence responses, such as sample presentation order, testing environment, and instructions provided. To minimize fatigue and sensory adaptation effects, it is recommended to limit the number of samples per session (ideally 4–6 in FP and FCP, and up to 8 in CATA and Napping®) and to implement balanced and randomized designs [5]. The use of references or anchors (e.g., a control product in Pivot Profile) can improve response consistency, especially in comparative methods. Additionally, for techniques involving free description (FCP and FP), it is helpful to provide examples of descriptive terms to guide participants without imposing predefined language [9].

Data analysis must be tailored to the nature of each technique. For CATA, the most common approach includes calculating the frequency of term selection, followed by correspondence analysis (CA) or chi-square tests to identify discriminant attributes [1]. In the case of FP and FCP, where descriptors are heterogeneous, techniques such as Generalized Procrustes Analysis (GPA) or Multiple Factor Analysis (MFA) are used to integrate and compare individual profiles [14]. For Napping®, MFA is the preferred tool to visualize product groupings in a two-dimensional space, complemented by cluster analysis when identifying consumer segments is of interest [25]. In all cases, the use of specialized software (e.g., XLSTAT, R, and SensoMineR) facilitates the processing of complex data and the generation of interpretable visualizations [29].

The interpretation of results must consider the inherent limitations of each method. For example, in CATA, the list of terms may influence responses, so it is recommended to validate the list beforehand through focus groups or pilot testing [4]. In FP and FCP, subjectivity in descriptor generation can introduce noise; therefore, semantic grouping techniques (e.g., grouping “sweet” and “sugary” as synonyms) can improve clarity [3]. The integration of rapid methods with hedonic tests or intensity scales (e.g., CATA with intensity ratings) can enrich the findings, especially in product reformulation studies [12]. In summary, although these techniques offer agility, their rigorous application requires attention to methodological details to

Method	Consumer	Statistical analysis	Advantages	Limitations
CATA	50–100	• Selection frequencies • Chi-square • Correspondence analysis (CA)	• Fast and easy to implement • No training required • Quantifiable data	• List of terms can bias results • Less sensitive to subtle differences
Free Choice Profile (FCP)	10–20 (familiar with the product)	• Generalized Procrustes Analysis (GPA) • Multiple Factor Analysis (MFA)	• Captures individual perceptions • Useful for complex products • Efficient discrimination between similar products	• Complex analysis due to term heterogeneity • Redundancy in descriptors • Requires product familiarity
Flash Profile (FP)	10–20 (familiar with the product)	• GPA • MFA • Clustering	• Results in 1 or 2 sessions	• Advanced multivariate analysis
Pivot Profile	15–30	• GPA • Consensus analysis	• Detection of specific differences • Ideal for reformulations	• Depends on the choice of the pivot product • Less effective with minimal differences
Napping®	50–100	• MFA • ANOVA • Clustering	• Holistic view of similarities • Suitable for consumers	• Subjective if the task is not understood • Advanced multivariate analysis

Table 1.
Comparison of rapid descriptive sensory analysis methods.

ensure that the data obtained is both reliable and actionable in food development and optimization.

4. Case study

This chapter includes a sensory evaluation of muffins made with different combinations of purple corn flour and kiwicha flour. The objective was to compare three rapid descriptive sensory analysis methods: Free Choice Profile (FCP), Flash Profile (FP), and Check-All-That-Apply (CATA).

4.1 Materials and methods

4.1.1 Sample

Six muffin formulations were developed. The formulations varied in the proportion of purple corn flour (PCF) and kiwicha flour (KF), using a completely randomized design. The combinations were as follows: S1 (100 g PCF), S2 (25 g PCF– 75 g KF), S3 (50 g PCF – 50 g KF), S4 (75 g PCF – 25 g KF), S5 (100 g KF), and S6 (100 g wheat flour, as a control sample). All other ingredients were kept constant per batch: white sugar (650 g), whole milk (850 g), eggs (650 g), baking powder (70 g), cocoa powder (50 g), and vegetable oil (650 g).

4.1.2 Consumers

A total of 130 consumers participated in the sensory evaluation, all university students over 18 years old, distributed according to the methodology employed: 15 for Free Choice Profile, 15 for Flash Profile, and 100 consumers for the CATA method. The samples, each weighing 20 g, were served at room temperature ($22 \pm 1^\circ\text{C}$) in disposable containers coded with random three-digit numbers under controlled white lighting. Participants were given clear instructions on how to evaluate the sensory attributes using specific sensory references [30], and were instructed to rinse their palates with mineral water between samples.

4.1.3 Sensory testing

4.1.3.1 Free choice profiling

The Free Choice Profile method was applied in two stages to evaluate the muffins. In the first stage, untrained consumers freely generated sensory descriptors (flavor, texture, aroma, and appearance) for each sample, without a predefined list. In the second stage, the same panelists rated the intensity of the identified attributes across all samples using their own scales. The data were analyzed using Generalized Procrustes Analysis (GPA), which allowed individual perceptions to be aligned into a common sensory space, identifying relevant differences among the muffin formulations.

4.1.3.2 Flash profile

The Flash Profile method was implemented in two phases. In the first phase, panelists freely generated a list of perceived sensory attributes without any

predefined guidance, allowing for spontaneous identification of relevant descriptors [9]. This information was collected *via* individual forms. In the second phase, evaluators ranked the samples according to the intensity or presence of the previously identified attributes, allowing for a rapid comparative characterization of the formulations [6].

4.1.3.3 *Check-all-that-apply*

For this technique, a sensory evaluation form was designed based on a predefined list of sensory attributes to identify the perceptible characteristics of the products under study. Consumers were free to select all attributes they considered present in each sample [1]. A total of 21 sensory attributes were included, previously established in similar studies [31]: sweet, spongy, lumpy, gummy, dark, dry, bland, bitter, soft, moist, corn aroma, greasy, light flavor, sticky, gritty, vanilla aroma, porous, chocolate flavor, slightly sweet, and savory. The data were analyzed through frequency counts to determine the predominant sensory profile of each sample [7]. Printed forms were provided, and there was no limit on the number of attributes that could be selected per sample.

4.1.3.4 *Comparison of rapid methods*

To compare the sensory perceptions obtained using different methodologies applied to muffins, sensory maps generated through multivariate analysis were used. Subsequently, the RV coefficient was calculated to quantify the similarity between the sensory spaces generated by each method. This coefficient, which ranges from 0 (no relation) to 1 (perfect match), allowed the evaluation of the degree of agreement among the spatial configurations produced by the panelists across the different techniques. In this way, the consistency of the sensory characterization of the samples across the applied approaches was determined.

4.2 Results

4.2.1 *Free choice profiling*

Figure 1 presents the results obtained after applying the free choice profile method, where it is observed that the muffin formulations differed mainly along two sensory axes: sweetness-bitterness and texture-appearance. Samples with a higher proportion of purple corn flour (S1 and S4) were associated with attributes, such as “Dark”, “Bitter”, and “Soft”, reflecting the impact of phenolic compounds on color and flavor, while samples with kiwicha (S2 and S5) showed a higher frequency of terms such as “Dry” and “Sandy texture”, indicating challenges in moisture retention. On the other hand, the control with wheat flour (S6) and the balanced mixes (S3) were associated with “Sweet”, “Balanced flavor”, and “Attractive appearance”, highlighting their sensory preference. The comparison between “Sweet” and “Bitter” in the sensory space confirmed that these attributes were the main discriminators, while texture (“Soft” and “Sandy”) and odor (“Strong smell”) emerged as secondary but relevant factors. These results demonstrate that the FCP effectively captured individual perceptions, identifying both the strengths (e.g., uniqueness of purple corn) and limitations (e.g., dryness of kiwicha) of the alternative flours, providing valuable insights for optimizing formulations.

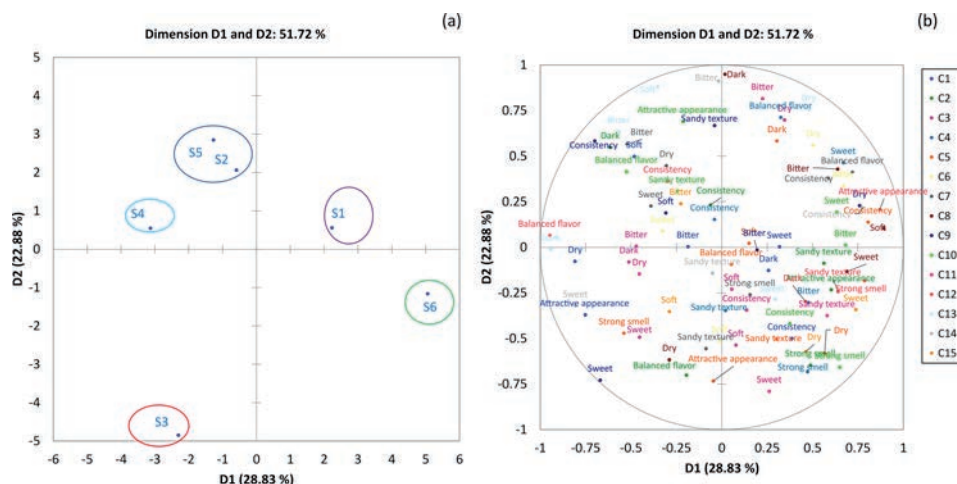


Figure 1.

Sensory map of the samples (a) and sensory attributes (b) obtained through the free choice profile.

4.2.2 Flash profile

The Flash Profile analysis reveals a clear sensory segmentation between the muffin formulations, as seen in **Figure 2**. The samples with the highest proportion of purple corn (S1 and S4) and the wheat control (S6) are grouped into a sector associated with positive attributes such as “attractive color,” “smooth texture,” and “balanced flavor,” while the kiwicha samples (S2 and S5) are concentrated in an area linked to less favorable characteristics such as “sandy texture” and “dryness.” The intermediate sample (S3) occupies a transitional position, reflecting its balanced composition. The most discriminating attributes (“intense odor,” “balanced flavor,” and “unpleasant flavor”) appear further from the center, confirming the method’s ability to identify key differences between formulations. Although some individual variability typical of free profile methods is observed, a consistent group pattern emerges associating purple corn with positive sensory qualities and kiwicha with textural challenges, highlighting the usefulness of Flash Profiling to rapidly characterize innovative products and guide their optimization, particularly in the development of balanced blends that combine the advantages of both ingredients.

4.2.3 CATA

Figure 3 presents the results of the CATA analysis in a biplot figure. CATA analysis revealed clear sensory differentiation between the muffin samples, with S1 (100% purple corn) and S6 (wheat control) associated with positive attributes such as “sweet,” “tasty,” “chocolate aroma,” and “moist texture,” highlighting their greater acceptability. In contrast, the kiwicha samples (S5 – 100% kiwicha and S2 – 25% purple corn/75% kiwicha) were strongly associated with negative characteristics such as “dry,” “gritty,” “bitter,” and “tasteless,” highlighting the main technological challenges of this flour. Sample S3 (50% purple corn/50% kiwicha) occupied an intermediate position, associated with “slightly sweet,” suggesting that balanced blends could

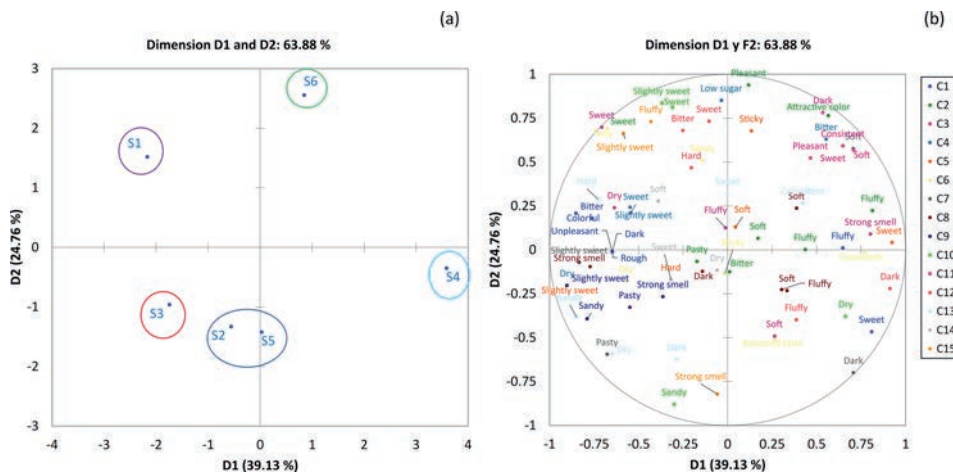


Figure 2.
Sensory map of the samples (a) and sensory attributes (b) obtained through the flash profile.

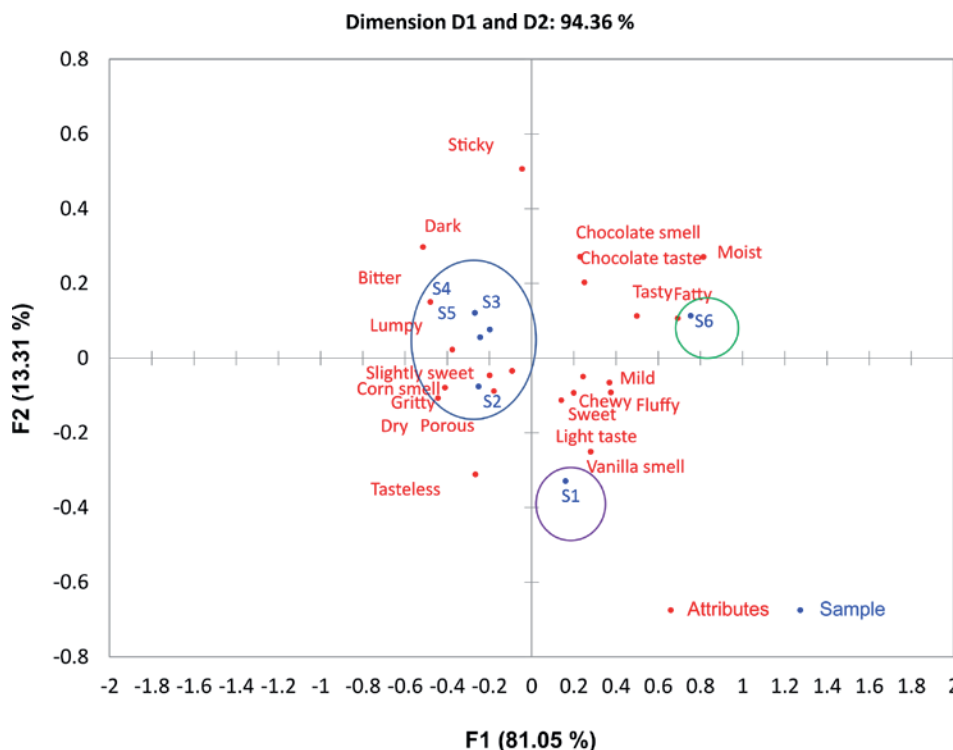


Figure 3.
Biplot sensory map of the samples and sensory attributes obtained using the CATA method.

mitigate the defects of pure kiwicha. The biplot confirmed that sweetness, absence of textural defects, and familiar aromas (chocolate/vanilla) were the key drivers of preference, while dryness and bitterness acted as the main rejections. These results, consistent with those obtained using FCP and Flash Profile, provide quantitative

evidence to guide reformulation, prioritizing texture improvement in kiwicha-based products and leveraging the positive notes of purple corn.

The three methods applied (Free Choice Profile, Flash Profile, and CATA) proved effective in differentiating muffin formulations, although with nuanced results. The Free Choice Profile (FCP) revealed detailed individual perceptions, identifying that purple corn samples (S1 and S4) were associated with attributes such as “dark” and “intense flavor,” while kiwicha samples (S2 and S5) were associated with “sandy texture” and “dryness.” However, the subjectivity of the free descriptors generated some variability. The Flash Profile (FP) confirmed these groupings, but with a more hierarchical structure, highlighting the polarization between purple corn samples (positive attributes such as “moist”) and kiwicha (negative attributes such as “grainy”), in addition to emphasizing the balancing role of S3. Its advantage was the speed of direct comparison, although it required panelists familiar with the products. In contrast, the CATA provided a clear quantification of attribute frequencies, confirming that “sweet,” “savory,” and “chocolatey” drove preference for S1 and S6, while “dry” and “flavorless” affected S5. Its strengths lie in its ease of application with untrained consumers and the collection of statistically robust data. The differences lay in the approach: the FCP offered qualitative depth, but with greater dispersion; the FP combined speed and a hierarchical structure, ideal for early stages of development; and the CATA provided quantitative and scalable data, optimal for validating preferences with large groups. While the FCP and FP allowed for the exploration of emerging descriptors (e.g., “earthy”), the CATA quantified their relevance. Overall, the triangulation of methods enriched the analysis, with the FCP and FP providing detailed insights for reformulation, and the CATA statistically validating the findings.

4.3 Comparison of rapid methods

Table 2 presents the results applying the RV coefficient to demonstrate the similarities between the sensory maps obtained from the different rapid descriptive tests: Free Choice Profile (FCP), Flash Profile (FP), and Check-All-That-Apply (CATA).

Sample	FCP		FP		CATA	
	D1	D2	D1	D2	D1	D2
S1	2.302	0.338	−2.167	1.517	0.161	−0.329
S2	0.051	−0.176	−0.557	−1.332	−0.251	−0.076
S3	−2.622	−3.459	−1.742	−0.965	−0.198	0.077
S4	−3.265	1.902	3.587	−0.351	−0.269	0.121
S5	−2.834	2.071	0.031	−1.424	−0.244	0.056
S6	6.368	−0.676	0.848	2.554	0.754	0.113
Method	RV coefficients		p-value			
FCP-FP	0.488		0.191			
FCP-CATA	0.852		0.016			
FP-CATA	0.525		0.125			

Table 2.
Results of the RV coefficient analysis.

Comparison using RV coefficients revealed that FCP and CATA had a high correlation (RV: 0.852; $p = 0.016$), validating their consistency in identifying similar samples, while FP showed less alignment with the other methods (RV: 0.488–0.525; $p > 0.05$) due to its hierarchical approach. This complementarity demonstrates that FCP/FP are ideal for exploring qualitative attributes, while CATA offers statistical robustness to validate preferences. Together, they enable a comprehensive characterization, essential for optimizing formulations with innovative ingredients.

5. Conclusions

Rapid descriptive sensory analysis methodologies (CATA, Free Choice Profile, Flash Profile, Pivot Profile, and Napping®) are valuable tools for the efficient evaluation of food products. Each technique has distinctive features that make it suitable for different research and product development contexts. CATA stands out for its ease of application with untrained consumers, while Flash Profile and Free Choice Profile offer greater descriptive depth when complex product characterization is required. Pivot Profile emerges as an ideal alternative for comparative studies using a reference sample, and Napping® provides a holistic view of relationships among samples. The rapid sensory analysis methods (FCP, FP, and CATA) proved to be complementary for evaluating muffins with alternative flours. While FCP and FP identified key qualitative attributes (such as texture and flavor), CATA quantified preferences with greater statistical rigor. The combination of these techniques allowed detecting both the advantages of purple corn (intense flavor) and the challenges of kiwicha (dryness), validating that balanced blends (such as T3) represent a promising alternative. This complementarity highlights the importance of selecting the method according to the objective: exploration (FCP/FP) or validation (CATA). The choice of the most appropriate method should be guided by three key factors: (1) the objective of the study (discrimination, description, or comparison), (2) the training level of the available panelists, and (3) the resources allocated for data analysis. The practical case with muffins demonstrated how complementary techniques can provide different perspectives on the same product. These methodologies are transforming the food industry by accelerating development cycles and enabling data-driven decision-making based on robust sensory evidence.

Acknowledgements

The authors express their sincere gratitude to the Vice Presidency for Research of the National University of Barranca for the financial support and backing provided for the development of these food studies (Grant No. 919-2023-UNAB).

Conflict of interest

The authors declare no conflict of interest.

Author details

Reynaldo Justino Silva-Paz^{1*}, Nicodemo Crescencio Jamanca-Gonzales¹,
Thalia Alexandra Rivera-Ashqui² and Amparo Eccoña-Sota³

1 Food Industry Engineering, Department of Engineering, National University of
Barranca, Lima, Peru

2 Faculty of Engineering and Architecture, Food Industry Engineering, Peruvian
Union University, Lima, Peru

3 Faculty of Veterinary Medicine and Animal Husbandry, Micaela Bastidas National
University of Apurímac, Abancay, Peru

*Address all correspondence to: rsilva@unab.edu.pe

IntechOpen

© 2025 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. 

References

- [1] Ares G, Jaeger SR. Check-all-that-apply (CATA) questions with consumers in practice: Experimental considerations and impact on outcome. In: Delarue J, Lawlor JB, editors. *Rapid Sensory Profiling Techniques*. Cambridge: Woodhead Publishing; 2023. pp. 257-280. DOI: 10.1016/B978-0-12-821936-2.00013-3
- [2] Lawless HT, Heymann H. *Sensory Evaluation of Food: Principles and Practices*. New York: Springer Science & Business Media; 2010
- [3] Varela P, Ares G. Sensory profiling, the blurred line between sensory and consumer science. A review of novel methods for product characterization. *Food Research International*. 2012;**48**(2):893-908. DOI: 10.1016/j.foodres.2012.06.037
- [4] Meyners M, Castura JC, Carr BT. Existing and new approaches for the analysis of CATA data. *Food Quality and Preference*. 2013;**30**(2):309-319. DOI: 10.1016/j.foodqual.2013.06.010
- [5] Jaeger SR, Chheang SL, Jin D, Roigard CM, Ares G. Check-all-that-apply (CATA) questions: Sensory term citation frequency reflects rated term intensity and applicability. *Food Quality and Preference*. 2020;**86**:103986. DOI: 10.1016/j.foodqual.2020.103986
- [6] Aguiar LAD, Melo L, de Lacerda de Oliveira L. Validation of rapid descriptive sensory methods against conventional descriptive analyses: A systematic review. *Critical Reviews in Food Science and Nutrition* 2019; **59**(16): 2535-2552. DOI: 10.1080/10408398.2018.1459468
- [7] Ares G, Tárrega A, Izquierdo L, Jaeger S. Investigation of the number of consumers necessary to obtain stable sample and descriptor configurations from check-all-that-apply (CATA) questions. *Food Quality and Preference*. 2014;**31**:135-141. DOI: 10.1016/j.foodqual.2013.08.012
- [8] Reinbach HC, Giacalone D, Ribeiro LM, Bredie WLP. Comparison of three sensory profiling methods based on consumer perception: CATA, CATA with intensity, and napping®. *Food Quality and Preference*. 2014;**32**:160-166. DOI: 10.1016/j.foodqual.2013.02.004
- [9] Delarue J, Sieffermann JM. Sensory mapping using flash profile. Comparison with a conventional descriptive method for the evaluation of the flavour of fruit dairy products. *Food Quality and Preference*. 2004;**15**(4):383-392. DOI: 10.1016/S0950-3293(03)00085-5
- [10] Dairou V, Sieffermann JM. A comparison of 14 jams characterized by conventional profile and a quick original method, the flash profile. *Journal of Food Science*. 2002;**67**(2):826-834. DOI: 10.1111/j.1365-2621.2002.tb10685.x
- [11] Meyners M, Castura JC. Randomization of CATA attributes: Should attribute lists be allocated to assessors or to samples? *Food Quality and Preference*. 2016;**48**:210-215. DOI: 10.1016/j.foodqual.2015.09.014
- [12] Torri L, Salini S. An itinerant sensory approach to investigate consumers' perception and acceptability at a food exhibition. *Food Research International*. 2016;**90**:91-99. DOI: 10.1016/j.foodres.2016.10.041
- [13] Perrin L, Symoneaux R, Maître I, Asselin C, Jourjon F, Pagès J. Comparison of three sensory methods for use with

the napping® procedure: Case of ten wines from Loire valley. *Food Quality and Preference*. 2008;**19**(1):1-11. DOI: 10.1016/j.foodqual.2007.06.005

[14] Dehlholm C, Brockhoff PB, Meinert L, Aaslyng MD, Bredie WLP. Rapid descriptive sensory methods – Comparison of free multiple sorting, partial napping, napping, flash profiling and conventional profiling. *Food Quality and Preference*. 2012;**26**(2):267-277. DOI: 10.1016/j.foodqual.2012.02.012

[15] Delarue J. Flash profile, its evolution and uses in sensory and consumer science. In: Delarue J, Lawlor JB, editors. *Rapid Sensory Profiling Techniques*. 2nd ed. Cambridge, UK: Woodhead Publishing; 2023. pp. 141-172. DOI: 10.1016/B978-0-12-821936-2.00025-X

[16] Moussaoui K, Varela P. Exploring consumer product profiling techniques and their linkage to a quantitative descriptive analysis. *Food Quality and Preference*. 2010;**21**(8):1088-1099. DOI: 10.1016/j.foodqual.2010.09.005

[17] Vidal L, Ares G, Giménez A. Projective techniques to uncover consumer perception: Application of three methodologies to ready-to-eat salads. *Food Quality and Preference*. 2013;**28**(1):1-7. DOI: 10.1016/j.foodqual.2012.08.005

[18] Ribeiro ACP, Magnani M, Freitas MQ, Esmerino EA, Cruz AG, Pimentel TC. Comparison of classic and emerging sensory methodologies. *Current Food Science and Technology Reports*. 2023;**1**(2):35-45. DOI: 10.1007/s43555-023-00005-5

[19] Spinelli S, Monteleone E, Ares G, Jaeger SR. Sensory drivers of product-elicited emotions are moderated by liking: Insights from

consumer segmentation. *Food Quality and Preference*. 2019;**78**:103725. DOI: 10.1016/j.foodqual.2019.103725

[20] Giacalone D, Clausen MP, Jaeger SR. Understanding barriers to consumption of plant-based foods and beverages: Insights from sensory and consumer science. *Current Opinion in Food Science*. 2022;**48**:100919. DOI: 10.1016/j.cofs.2022.100919

[21] Thuillier B, Valentin D, Marchal R, Dacremont C. Pivot© profile: A new descriptive method based on free description. *Food Quality and Preference*. 2015;**42**:66-77. DOI: 10.1016/j.foodqual.2014.11.010

[22] Pearson W, Schmidtke L, Francis IL, Blackman JW. An investigation of the pivot© profile sensory analysis method using wine experts: Comparison with descriptive analysis and results from two expert panels. *Food Quality and Preference*. 2020;**83**:103858. DOI: 10.1016/j.foodqual.2019.103858

[23] Thomas A, van Der Stelt AJ, Schlich P, Lawlor JB. Temporal drivers of liking for oral nutritional supplements for older adults throughout the day with monitoring of hunger and thirst status. *Food Quality and Preference*. 2018;**70**:40-48. DOI: 10.1016/j.foodqual.2017.05.001

[24] Jeong S, Lee J. Effects of cultural background on consumer perception and acceptability of foods and drinks: A review of latest cross-cultural studies. *Current Opinion in Food Science*. 2021;**42**:248-256. DOI: 10.1016/j.cofs.2021.07.004

[25] Pagès J. Collection and analysis of perceived product inter-distances using multiple factor analysis: Application to the study of 10 white wines from

the Loire Valley. Food Quality and Preference. 2005;**16**(7):642-649.
DOI: 10.1016/j.foodqual.2005.01.006

[26] Risvik E, McEwan JA, Colwill JS, Rogers R, Lyon DH. Projective mapping: A tool for sensory analysis and consumer research. Food Quality and Preference. 1994;**5**(4):263-269.
DOI: 10.1016/0950-3293(94)90051-5

[27] Hopfer H, Heymann H. Judging wine quality: Do we need experts, consumers or trained panelists? Food Quality and Preference. 2014;**32**(C):221-233.
DOI: 10.1016/j.foodqual.2013.10.004

[28] Jang J, Lee DW. Advancements in plant-based meat analogs enhancing sensory and nutritional attributes. npj Science of Food. 2024;**8**(1):50.
DOI: 10.1038/s41538-024-00292-9

[29] Lê S, Husson F. Sensominer: A package for sensory data analysis. Journal of Sensory Studies. 2008;**23**(1):14-25.
DOI: 10.1111/j.1745-459X.2007.00137.x

[30] Schouteten JJ, De Steur H, Lagast S, De Pelsmaecker S, Gellynck X. Emotional and sensory profiling by children and teenagers: A case study of the check-all-that-apply method on biscuits. Journal of Sensory Studies. 2017;**32**:e12249.
DOI: 10.1111/joss.12249

[31] Andersen NR, van Deurs PR, Frøst MB. Consumer interest in hummus made from different pulses: Effects of information about origin and variety seeking tendency. International Journal of Gastronomy and Food Science. 2022;**29**:100572. DOI: 10.1016/j.ijgfs.2022.100572

Perspective Chapter: Sensory Lifetime Optimization Using Artificial Intelligence

*Bianca Pio Ávila, Layla Damé Macedo
and Márcia Arocha Gularte*

Abstract

This chapter addresses the sensory shelf life of foods as a key determinant of consumer acceptance, exploring methods ranging from traditional approaches to the latest technological innovations. Survival analysis and the application of artificial intelligence emerge as promising tools for more efficient prediction of sensory rejection. Despite these advances, human perception and cultural variations continue to challenge the standardization of such evaluations. The chapter also highlights the importance of dynamic and personalized approaches, capable of reducing waste and enhancing consumer satisfaction, pointing toward a future where the integration of science, technology, and sensory perception will be crucial for the success of the food industry.

Keywords: machine learning, survival analysis, consumer, quality, cut-off point

1. Introduction

The advancement of science and technological development have profoundly transformed society, impacting not only communication and social interaction but also production systems and industrial processes. In the food sector, these innovations have driven a restructuring of traditional production and quality control methods, enabling the emergence of intelligent tools that enhance capabilities for analysis, prediction, and real-time decision-making [1].

Among these technologies, artificial intelligence (AI) stands out as a branch of computer science that enables systems to learn and perform tasks typically associated with human intelligence, such as speech recognition, decision-making, and visual perception. In the industry, AI allows producers to understand data generated by their factories, operations, and consumers, transforming this data into meaningful decisions [2].

It is important to highlight that the enabler allowing AI systems to exhibit aspects of human intelligence is machine learning, which, in its most basic form, refers to the use of algorithms to analyze and learn from data in order to make decisions about specific tasks. Instead of explicitly programming a machine to perform a task,

machine learning algorithms enable the machine to learn how to perform the task by training the system through large amounts of data [3]. This massive data collection, coupled with the use of innovative technologies such as AI and algorithms to gather these data, provides essential insights for the expansion of the industrial sector.

In the context of food quality, sensory evaluation remains one of the most critical and challenging stages, as it involves the subjective perception of attributes such as flavor, aroma, texture, and appearance, which are directly related to product acceptability [4]. Although microbiological safety is essential for commercialization, it is often sensory perception that ultimately determines the market success of a food product. Therefore, understanding how these attributes evolve over time is fundamental, especially in perishable products. However, a common issue faced by industries is that foods may be microbiologically safe and within the expiration date but no longer accepted by consumers.

Sensory shelf life is defined as the period during which a food maintains sensory characteristics desirable to consumers, constituting a practical need for the food industry. However, this process involves numerous environmental and formulation variables, making its estimation complex. Frequently, foods that are still safe for consumption may present undesirable sensory changes leading to consumer rejection, causing waste and economic losses [5].

Although defining the shelf life of perishable food products may seem straightforward, it is a complex task involving factors of food safety and quality affected by distribution and storage conditions. Shelf-life limits based on various factors established by regulatory agencies are determined at the laboratory level without consumer involvement. In shelf-life definitions, the limit of sensory properties is referred to as acceptable/unacceptable or desired/intended. These limits can be highly ambiguous if not thoroughly researched. Industries that need to comply with food regulations and, more importantly, meet quality standards require practical and reliable methods to estimate the shelf life of their products to also meet consumer expectations [6].

Shelf-life limits are established considering various parameters defined by regulatory agencies, usually based on laboratory analyses and often without directly addressing consumer perception. The definition of the expiration date concerning sensory properties is typically expressed in terms of acceptability or rejection, but these criteria can be quite subjective if not supported by thorough research. Therefore, industries need reliable and practical methods to estimate product shelf life that ensure regulatory compliance and consumer satisfaction [6].

Thus, it becomes essential to evaluate how artificial intelligence and machine learning models can be applied to predict food shelf life by integrating physicochemical and sensory data to provide a more robust and accurate analysis.

2. Food shelf life

Food shelf life refers to the period during which a product maintains satisfactory quality and safety conditions for consumption, as specified by the manufacturer. This concept encompasses both microbiological safety and the preservation of sensory and nutritional characteristics, influenced by factors such as food composition, manufacturing processes, packaging type, and storage conditions [7].

Food deterioration results from a complex combination of intrinsic and extrinsic factors acting simultaneously. Among the intrinsic factors, the following stand out:

- Water activity (A_w), which impacts microbial growth;
- pH and total acidity, affecting chemical and microbiological stability;
- Redox potential (E_h), influencing chemical and biological reactions;
- Oxygen availability, a factor that can accelerate oxidative processes;
- Presence of nutrients, which favors microbial development;
- Natural microflora of the food, including bacteria, fungi, and yeasts;
- Natural biochemical components, such as enzymes and internal reactions;
- Use of preservatives and additives that extend shelf life.

Extrinsic factors relate to environmental and operational conditions the food encounters throughout the supply chain, such as:

- Time and temperature during processing;
- Internal pressure within packaging;
- Temperature control during transport and storage;
- Relative humidity during production and storage;
- Exposure to light at various stages;
- Microbial contamination of the environment;
- Composition of the atmosphere inside the packaging;
- Subsequent thermal treatments;
- Handling and use by the final consumer.

The interaction between these factors determines whether a food product will maintain its quality for a longer time and remain acceptable to consumers.

Moreover, shelf-life definition must consider the relationship between sensory deterioration and microbiological stability. Often, food remains microbiologically safe but is rejected due to sensory changes such as alterations in color, texture, or flavor. Hence, the concept of sensory shelf life has gained increasing importance in the food industry [5].

To meet regulatory and market demands, modern approaches have been adopted in shelf-life assessment, including mathematical modeling, predictive analyses, and simulations based on real data. Technologies such as smart sensors, the Internet of Things (IoT), and artificial intelligence enable more precise prediction of when a food product will become unacceptable, considering variability in logistics and production conditions [8, 9].

Shelf-life studies should be tailored to the specific type of food, as deterioration mechanisms vary. For example, products rich in lipids may have oxidative rancidity as the main limiting factor, while fermented beverages may experience significant changes in pH and turbidity. These factors should be monitored alongside sensory attributes to ensure the product maintains its appeal to consumers throughout its valid period [6].

2.1 Shelf-life stability

The shelf life of a food product is the period between its production and the point at which it becomes unfit for consumption, considering storage and distribution conditions. Storage and distribution are essential stages in the food supply chain, and the quality of the product determines how long it can remain in these stages before deteriorating. However, quality loss typically occurs gradually [10].

To ensure that a food product reaches the consumer safely and with high quality, a total quality approach must be adopted, which includes:

- Product design (including risk analysis to ensure safety);
- Selection and testing of ingredients and packaging;
- Manufacturing processes;
- Transportation, storage, and retail display;
- Home storage and consumption.

Since food must be safe and of acceptable quality at the time of consumption, defining shelf life is a crucial part of product development. This control is required by Good Manufacturing Practices (GMP) and the international quality management standard ISO 9001.

Determining the shelf life of a new product often requires extended testing, including samples from the early development stages through the initial production batches.

2.2 Regulation

In Brazil, regulations on shelf life have evolved significantly since the 1980s, when the first guidelines for food and beverage labeling were established [11]. A major milestone occurred in 2018, when Anvisa published Guideline No. 16, a reference document for determining shelf life with an emphasis on health and safety issues [12]. Currently, the Brazilian Health Regulatory Agency (Anvisa) [12, 13] enforces technical requirements for the labeling of packaged foods, reflecting the increasing complexity of the sector.

The traditional evaluation method—based on microbiological and physicochemical analyses complemented by sensory tests with trained panels—has shown limitations throughout the year [14]. Although methods such as Quantitative Descriptive Analysis and discriminative tests provide analytical precision, their predictive capacity for real consumer acceptance remains questionable [6]. This gap becomes especially evident when considering that approximately 30% of food is globally discarded due to sensory rejection, even though it is still safe for consumption [15]. Survival analysis emerges as a transformative statistical tool in this context, allowing

the modeling of temporal acceptance curves through methods such as Kaplan-Meier and Cox regression, which elegantly incorporate censored data and environmental covariates [16, 17].

In contrast, the European Union has one of the most advanced regulatory systems, based on Regulation (EU) No. 1169/2011, which clearly distinguishes between “best before” dates for stable products and “use by” dates for perishables. The European Food Safety Authority (EFSA) not only establishes rigorous scientific criteria but also mandates the validation of sensory methods for specific food categories, following standards such as ISO 13299:2016. Furthermore, the Farm to Fork Strategy, launched in 2020, integrates shelf-life management into sustainability policies aimed at reducing food waste throughout the production chain [18–20].

The United States adopts a pragmatic approach, with the FDA and USDA regulating specific sectors of the food industry. While the FDA Food Code provides general guidelines, the USDA requires strict scientific validation for meat and dairy products. A distinguishing feature of the American market is the widespread adoption of predictive technologies, such as the Pathogen Modeling Program (PMP), which simulates food spoilage based on environmental variables. Innovative companies have implemented solutions such as blockchain to track shelf life in real-time, demonstrating how technology can transform quality management [21–24].

In Asia, Japan stands out for the strictness of its system, where the Food Sanitation Act requires accelerated testing combined with real storage to substantiate shelf-life claims. China, in turn, follows GB 7718-2011, aligned with Codex Alimentarius recommendations, though it faces challenges in enforcement due to the scale and regional diversity of its food production [25–27].

Globally, there is a trend toward regulatory convergence driven by international bodies such as the Codex Alimentarius, but regional differences still persist. Emerging technologies—including artificial intelligence and the Internet of Things—are revolutionizing shelf-life estimation by enabling dynamic models that consider variables such as transportation and storage conditions. Simultaneously, sustainability concerns have led countries like France to implement anti-food waste legislation, creating new paradigms for shelf-life management. In the Brazilian context, adopting such innovations could represent significant progress, particularly in integrating food safety, sensory acceptance, and sustainability [14, 17, 28].

2.3 Direct and indirect methods for shelf-life determination of foods

Shelf-life evaluation aims to predict how foods behave in physicochemical and enzymatic reactions responsible for deterioration, which are more rapidly detected through changes in color, odor, texture, viscosity, and lipid oxidation, among other characteristics [21].

Traditionally, sensory shelf-life estimation focuses on ensuring that minimal sensory changes occur in products during storage.

Perceptible difference tests, defined as the time required for consumers to distinguish the test product from the fresh product, can include:

- Descriptive Profile Analysis of the fresh product;
- Acceptance testing to measure overall consumer rejection scores or willingness to purchase the product. In other words, the period during which the product is still accepted by consumers as having the expected quality level.

Consumer testing has been considered the most appropriate tool to determine the sensory shelf life of food products. For this reason, reference [6] recommends using consumer-based information to determine the maximum tolerable deterioration and suggest the application of consumer tests—or the combination of analytical and hedonic sensory tests—rather than relying solely on quality analysis performed by trained panels.

Classical discriminative and descriptive methods are used to evaluate changes over time in sensory quality or in the intensity of key attributes responsible for product deterioration. These tests are traditionally conducted with trained sensory panels, whose members must be recruited and selected based on their sensory acuity and their ability to detect differences between samples [21]. In the context of sensory shelf-life estimation, three tests have been widely applied: difference from control, overall quality rating, and intensity quantification of sensory attributes.

Two main approaches are most commonly used for sensory shelf-life estimation: the acceptability limit approach and survival analysis. Both require large groups of consumers, who must be selected to represent the target population and evaluate the samples based on their own perception.

3. Artificial intelligence and survival analysis

Artificial intelligence (AI) can be defined as a field of computer science that aims to develop systems capable of performing tasks that traditionally require human intelligence. These systems are designed to learn, reason, perceive, make decisions, and solve problems autonomously or semi-autonomously [29].

AI and machine learning (ML) are revolutionizing scientific research, offering powerful tools for data analysis, pattern recognition, and process optimization. These technologies not only enhance traditional processes but also open new research frontiers, enabling the analysis of complex datasets, the discovery of nontrivial patterns, and the automation of experiments that previously required years of manual work. This article explores how AI and ML are being applied across different scientific domains, highlighting their impact, challenges, and future perspectives.

One of the greatest challenges in contemporary science is the efficient processing of large volumes of data, generated by highly complex experiments or large-scale observations. ML techniques, such as convolutional neural networks (CNNs) and unsupervised learning algorithms, have proven essential for extracting relevant information from massive datasets [30].

Beyond data analysis, AI is transforming how new hypotheses are formulated and tested. In chemistry and materials science, generative algorithms—such as Generative Adversarial Networks (GANs)—are used to design molecules with specific properties, dramatically reducing the time required for the development of new pharmaceuticals. Similarly, reinforcement learning (RL) techniques have been applied to optimize chemical reactions, enabling the synthesis of compounds with greater energy efficiency and lower environmental impact [31].

Despite these advances, the application of AI in scientific research is not without challenges. Model interpretability remains a critical issue, as many ML algorithms operate as “black boxes,” making it difficult to understand how decisions are made. Additionally, the quality and representativeness of training data can introduce biases that compromise the validity of results.

The integration of AI and ML in scientific research represents a transformative paradigm, capable of accelerating discoveries, reducing costs, and enabling innovative approaches. However, to fully realize this potential, it is essential to address technical and ethical challenges, ensuring that these technologies are applied transparently and responsibly. As AI continues to evolve, its role in science is expected to expand, opening up new possibilities for understanding the natural world and solving global challenges.

Machine learning (ML) is a subfield of AI focused on developing algorithms that allow computers to learn from data without being explicitly programmed for each task. Instead of following predefined rules, ML models identify patterns, make predictions, and improve performance through experience (i.e., training data) [32].

ML can be categorized into three main types:

1. Supervised learning—Models are trained on labeled data (e.g., classifying images as “cat” or “dog”). Examples: linear regression, neural networks.
2. Unsupervised learning—Models detect patterns in unlabeled data (e.g., clustering customers by behavior). Examples: clustering algorithms (K-means), dimensionality reduction (PCA).
3. Reinforcement learning—Models learn through trial and error, receiving rewards or penalties (e.g., robots learning to walk, games like AlphaGo).

Within ML, deep learning is a subfield based on artificial neural networks with multiple layers, enabling the processing of complex and high-dimensional data. This technique laid the foundation for the first survival analysis models using AI.

Statistical survival analysis, also known as time-to-event modeling, encompasses methods developed to study phenomena where the primary interest lies in the time interval between an initial point (e.g., diagnosis or treatment start) and the occurrence of an event of interest (e.g., relapse, failure, or recovery). This approach is especially relevant for handling incomplete data, such as truncated observations (limited by selection criteria) or censored data (when the event does not occur during the study period), enabling robust statistical modeling despite partial information [33].

Unlike traditional techniques, survival analysis accounts for the dynamic nature and uncertainty inherent in temporal processes. For example, in clinical studies, it can assess the time to death or clinical recovery, while in engineering, it evaluates the durability of components until equipment failure. Its flexibility makes it suitable for use in epidemiology, ecology, and social sciences, wherever temporal interpretation and risk estimation are required.

Even today, well-established techniques such as the Kaplan-Meier estimator (developed in 1958) and Cox proportional hazards regression (1972) remain fundamental tools in survival analysis. Only since the 2000s have ML algorithms begun to be adapted to temporal contexts, with methods such as Random Survival Forests and boosting techniques showing greater accuracy and flexibility than classical models [16].

Although neural networks have been used for several years, their complexity was limited by the lack of computational power. It was only from 2010 onward that Deep Learning models became more robust and applicable to heterogeneous and large-scale data.

The Kaplan-Meier estimator is a nonparametric method used to estimate the survival function $S(t)$, which represents the probability that a subject “survives”

(i.e., does not experience the event of interest) beyond time t . It is ideal for censored data, where not all individuals experience the event during the study period. This method is useful for estimating overall survival or comparing subgroups without adjusting for covariates. The result is a stepwise curve that decreases at each event occurrence.

The Cox Regression Model, also known as the Proportional Hazards Model, is a semi-parametric method that relates explanatory variables (covariates) to the hazard of event occurrence over time. Its key assumption is proportional hazards, meaning the effect of covariates is constant over time. It is widely used to identify risk factors or predictors associated with time to event [17].

Both Kaplan-Meier and Cox models are widely used in food quality studies, particularly in shelf-life estimation, product degradation, and evaluation of factors influencing stability or spoilage.

The Kaplan-Meier model can estimate the probability that a food remains suitable for consumption over time. For instance, in a bread shelf-life study, the “event” might be the appearance of mold, and censored observations would be those removed from the study before spoilage. The method allows for comparing the effectiveness of different preservation methods (e.g., vacuum vs. modified atmosphere packaging) [34].

Cox regression models can identify risk factors for spoilage. Variables such as storage temperature, humidity, pH, or preservative concentration can be analyzed as covariates to quantify their impact on the hazard of deterioration [35, 36].

Originally developed for clinical trials, survival analysis is gaining relevance in food science as a robust method for estimating sensory shelf life. Sensory shelf life refers to the period during which a product maintains organoleptic characteristics acceptable to consumers, such as aroma, taste, texture, and appearance. Traditionally, physicochemical and microbiological methods dominated this evaluation, but their inability to capture human perception motivated the adoption of survival models. This technique-adapted from biomedical studies-enables the modeling of time to

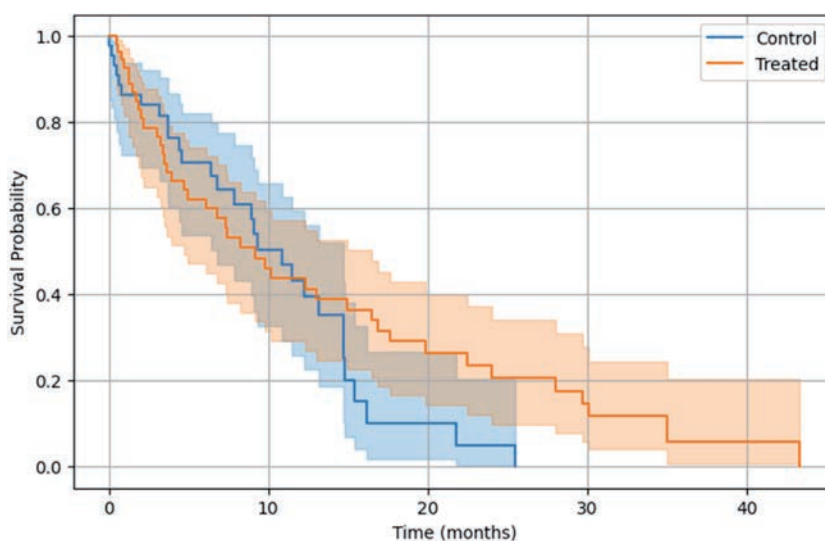


Figure 1.
Kaplan-Meier survival curve by group. Fonte: Autor (2025).

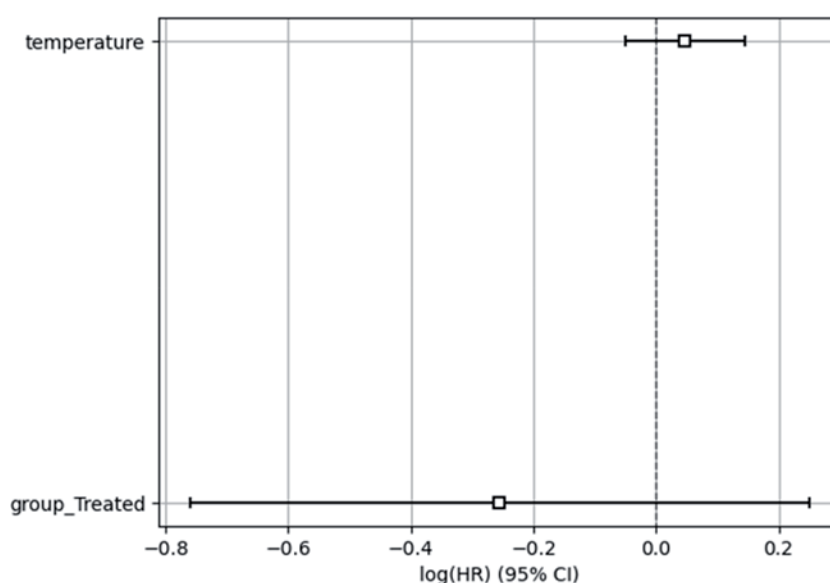


Figure 2.
 Cox model—covariate effects. Fonte: Autor (2025).

sensory rejection, incorporating censored samples (not deteriorated by the end of the study) and multiple variables (e.g., temperature, pH, packaging) [37, 38].

Figures 1 and 2 illustrate the Kaplan-Meier and Cox regression models. **Figure 1** shows on the Y-axis (vertical) the survival probability—that is, the likelihood that the food has not spoiled by a given time. The X-axis (horizontal) represents time (e.g., days or months), and each line represents a different group. **Figure 2** displays the impact of each covariate on the hazard of the event. Horizontal bars represent the regression coefficients, with bars to the right of zero indicating an increased risk of spoilage, and bars to the left indicating a reduced risk.

4. Sensory life time

The sensory shelf life of a food product refers to the period during which it retains acceptable sensory characteristics—such as aroma, flavor, texture, and appearance—that meet consumer expectations. While food safety and physicochemical stability are crucial aspects in determining the overall shelf life of a food, sensory acceptance plays a decisive role in the product's market success. Accurate determination of sensory shelf life requires robust methodologies that consider not only laboratory parameters but also human perception and consumer experience [6].

Traditionally, the estimation of sensory shelf life involves conducting both analytical and hedonic sensory tests, performed by trained panels and consumers. Classical methods include descriptive analyses, discriminative tests, and acceptance evaluations, which help identify the sensory rejection point over time. Among the most commonly used procedures are difference-from-control tests, which detect subtle changes between samples, and acceptance tests, where consumers express their willingness to continue consuming the product [34]. However, these methods present significant limitations, such as high costs, the need for recruiting and training

evaluators, and the difficulty in capturing real consumer perception under dynamic market conditions.

To overcome these limitations, more advanced techniques such as sensory survival analysis have gained prominence. This statistical approach, originally adapted from the medical field, enables modeling of time-to-rejection based on censored sensory data, taking into account variables that affect acceptance, such as storage temperature, packaging type, and intrinsic product characteristics [16, 17]. The Kaplan-Meier model estimates the sensory survival function by calculating the probability that a product remains acceptable over time, while the Cox regression model identifies factors that accelerate sensory deterioration. Studies on refrigerated products, such as fish burgers, have shown that this technique can reduce the time required to determine sensory shelf life by up to 30% compared to conventional methods [38].

Beyond survival analysis, the technological revolution has introduced innovative tools into sensory evaluation. Smart sensors, such as electronic noses and tongues, allow for continuous monitoring of volatile compounds and flavor profile changes, while hyperspectral imaging techniques assess color and texture changes noninvasively. Artificial intelligence has proven promising in integrating sensory, environmental, and compositional data, with machine learning algorithms and convolutional neural networks providing greater accuracy in predicting sensory shelf life. Augmented reality platforms and remote testing have also been explored to collect large-scale sensory responses, capturing the geographic and cultural diversity of preferences [34].

In the Brazilian context, where cultural diversity strongly influences sensory preferences, the adoption of these innovations presents both opportunities and challenges. On the one hand, rapid techniques such as NIR spectroscopy have gained traction in quality monitoring, and research combining traditional sensory analysis with computational methods is expanding. On the other hand, challenges remain in standardizing methods across industries and in providing technical training for implementing these technologies. Emerging trends—such as active packaging with sensory freshness indicators and crowdsourcing platforms for consumer perception data—point to a future where sensory shelf life will become increasingly dynamic and personalized [39, 40].

In conclusion, sensory shelf life is undergoing a paradigmatic shift—from static, generic evaluations to dynamic, predictive, and personalized models. This holistic approach, which integrates real-time monitoring, advanced modeling, and consideration of consumer preferences, not only extends sensory shelf life but also reduces waste and increases consumer satisfaction. To fully realize this potential in Brazil, greater collaboration between academia, industry, and regulatory agencies is essential, along with investment in the development of standardized protocols and professional training. In this way, the Brazilian food industry can align quality, safety, and sensory acceptance, delivering products that meet consumer expectations and remain competitive in the global market [28].

5. Conclusions

Sensory shelf life is essential for the success of the food industry, going beyond microbiological safety and physicochemical stability to focus on consumer acceptance. The evolution of methodologies—from traditional techniques to innovative approaches such as survival analysis and artificial intelligence—has enabled more

accurate prediction of sensory rejection, reducing evaluation time and costs. The future of shelf life lies in the integration of real-time monitoring, predictive modeling, and personalization, aiming not only to extend product longevity but also to minimize waste and align products with consumer expectations, thus ensuring quality and competitiveness in the global market.

In summary, the application of artificial intelligence in shelf-life prediction is both viable and essential, as it accelerates the process, fosters data-driven innovation, and supports more assertive decision-making. In this context, AI automates screening steps and aids in determining cutoff points with a focus on delivering consumer-oriented quality.

Acknowledgements

We appreciate the Federal University of Pelotas (UFPEL) for the support received during the production of this work and the research funding agencies, National Council for Scientific and Technological Development (CNPq) and Foundation for Research Support of the State of Rio Grande do Sul (FAPERGS). We also thank the authors of the works cited for sharing the scientific knowledge produced.

Conflict of interest

The authors declare no conflict of interest.

Author details

Bianca Pio Ávila, Layla Damé Macedo and Márcia Arocha Gulate*
Center for Chemical, Pharmaceutical, and Food Sciences, Sensory Analysis
Laboratory, Federal University of Pelotas, Pelotas, Brazil

*Address all correspondence to: marciagulate@hotmail.com

IntechOpen

© 2025 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. 

References

- [1] Manjula R, Narasamma B, Shruthi G, Nagarathna K, Kumar G. Artificial olfaction for detection and classification of gases using E-nose and machine learning for industrial application. In: Ghosh U, Maleh Y, Alazab M, Pathan ASK, editors. *Machine Intelligence and Data Analytics for Sustainable Future Smart Cities*. Cham: Springer; 2021. pp. 35-48
- [2] LeCun Y, Bengio Y, Hinton G. Deep learning. *Nature*. 2015;**521**(7553):436-444
- [3] Ludermir TB. Artificial intelligence and machine learning: Current state and trends. *Artificial Intelligence – Advanced Studies*. 2021;**35**(101):85-94. DOI: 10.1590/s0103-4014.2021.35101.007
- [4] Shehzad K. Predictive AI models for food spoilage and shelf-life estimation. *Global Trends in Science and Technology*. 2025;**1**(1):75-94. DOI: 10.70445/gtst.1.1.2025.75-94
- [5] Hough G, Garitta L. Methodology for sensory shelf-life estimation: A review. *Journal of Sensory Studies*. 2012;**27**:137-147
- [6] Hough G. *Sensory Shelf-Life Estimation of Food Products*. London: Taylor & Francis; 2010. 255 p
- [7] Espinoza TT, Quevedo R, Diaz O. Un Indicator values for food shelf-life prediction: A review. *Scientia Agropecuaria*. 2024;**15**:429-448. DOI: 10.17268/sci.agropecu.2024.032
- [8] Guo XG, He TY, Zhang ZX, Luo AX, Wang F, Ng EJ, et al. Artificial intelligence-enabled caregiving walking stick powered by ultra-low-frequency human motion. *ACS Nano*. 2021;**15**:19054-19069. DOI: 10.1021/acsnano.1c04464
- [9] Wan TQ, Shao BJ, Ma SJ, Zhou Y, Li Q, Chai Y. Insensor computing: Materials, devices, and integration technologies. *Advanced Materials*. 2023;**35**(37):e2203830
- [10] Ziyaina M, Rasco B, Coffey T, Ünlü G, Sablani SS. Colormetric detection of volatile organic compounds for shelf-life monitoring of milk. *Food Control*. 2019;**100**(June):220-226. DOI: 10.1016/j.foodcont.2019.01.018
- [11] CISA/BRASIL. Comissão Interministerial de Saúde e Agricultura. Resolução CISA/MA/MS nº 10, de 31 de julho de 1984. Dispõe sobre instruções para conservação nas fases de transporte, comercialização e consumo dos alimentos perecíveis, industrializados ou beneficiados, acondicionados em embalagens. *Diário Oficial da União*: seção 1, Brasília, DF, 1 ago. 1984
- [12] ANVISA. Resolução da Diretoria Colegiada da Anvisa—RDC n. 259, de 20 de Setembro de 2002. Regulamento Técnico para Rotulagem de Alimentos Embalados. Brazil: Agência Nacional de Vigilância Sanitária
- [13] ANVISA. Resolução da Diretoria Colegiada da Anvisa—RDC Nº 727, de 1º de Julho de 2022. Dispõe Sobre a Rotulagem dos Alimentos Embalados. Brazil: Agência Nacional de Vigilância Sanitária
- [14] Stone H, Sidel JL. *Sensory Evaluation Practices*. London: Elsevier Academic Press; 2004
- [15] FAO. *The State of Food and Agriculture 2019. Moving Forward on Food Loss and Waste Reduction*. Rome: Food and Agriculture Organization of the United Nations; 2019. DOI: 10.4060/ca6030en

- [16] Kaplan EL, Meier P. Nonparametric estimation from incomplete observations. *Journal of the American Statistical Association*. 1958;**53**:457-481
- [17] Cox DR. Regression models and life-tables. *Journal of the Royal Statistical Society: Series B: Methodological*. 1972;**34**:187-202
- [18] European Commission. Regulation (EU) No 1169/2011 of the European Parliament and of the Council of 25 October 2011 on the provision of food information to consumers. *Official Journal of the European Union*. L 304/18. 22 Nov 2011. Available from: <https://eur-lex.europa.eu/legal-content/PT/TXT/?uri=CELEX:32011R1169EUROPEAN UNION>
- [19] European Committee for Standardization. ISO 13299:2016: Sensory Analysis—Methodology—General Guidance for Establishing a Sensory Profile. Geneva: International Organization for Standardization; 2016
- [20] European Commission. Farm to Fork Strategy: For a Fair, Healthy and Environmentally-Friendly Food System. 2020. Available from: https://food.ec.europa.eu/horizontal-topics/farm-fork-strategy_en
- [21] U.S. Food and Drug Administration. General Guidelines Provided by the FDA for Food Safety. Food Code 2022. 2022. Available from: <https://www.fda.gov/media/164194/download>
- [22] U.S. Department of Agriculture, Agricultural Research Service. Pathogen Modeling Program (PMP) Online. n.d. Available from: <https://pmp.errc.ars.usda.gov/pmponline.aspx>
- [23] U.S. Department of Agriculture, Food Safety and Inspection Service. HACCP Validation. n.d. Available from: <https://www.fsis.usda.gov/inspection/compliance-guidance/haccp/haccp-validation>
- [24] World Economic Forum. How Blockchain Tracks Food across the Supply Chain and Saves Lives. 2024. Available from: <https://www.weforum.org/stories/2024/08/blockchain-food-supply-chain/>
- [25] Ministry of Health, Labour and Welfare of Japan. Outline of the Act Partially Amending the Food Sanitation Act. 2018. Available from: <https://www.mhlw.go.jp/content/11130500/000537821.pdf>
- [26] National Health Commission of the People's Republic of China. GB 7718- 2011: General Standard for the Labeling of Prepackaged Foods. Issued by the Ministry of Health of the People's Republic of China. China; 2011
- [27] Huang H. Comparative analysis of pre-packaged food labeling regulations between China, the European Union, and the United States. *Lecture Notes in Education Psychology and Public Media*. 2024;**77**(1):102-108. DOI: 10.54254/2753-7048/2024.18495
- [28] Giménez A, Ares G. Sensory shelf-life estimation. In: *Food Quality and Shelf Life*. Cambridge, Massachusetts, EUA: Academic Press; 2019. pp. 333-357. DOI: 10.1016/b978-0-12-817190-5.00011-2
- [29] Khaleel M, Jebrel A, Shwehdy D. Artificial intelligence in computer science. *International Journal of Electrical Engineering and Sustainability*. 2024;**2**:1-21
- [30] Alzubaidi L, Zhang J, Humaidi AJ, et al. Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data*. 2021;**8**:53. DOI: 10.1186/s40537-021-00444-8

- [31] Zagorodna N, Stadnyk M, Lypa B, Gavrylov M, Kozak R. Network attack detection using machine learning methods. Challenges to National Defence in Contemporary Geopolitical Situation. 2022;**2022**(1):55-61. DOI: 10.47459/cndcgs.2022.7
- [32] Chaudhary I, Adhikari S. Ransomware detection using machine learning techniques. Researcher CAB: A Journal for Research and Development. 2024;**3**:96-114. DOI: 10.3126/rcab.v3i1.68424
- [33] Gámbaro A, Ares G, Giménez A. Shelf-life estimation of apple-baby food. Journal of Sensory Studies. 2006;**21**:101-111. DOI: 10.1111/j.1745-459X.2006.00053.x
- [34] Ishwaran H, Kogalur UB, Blackstone EH, Lauer MS, et al. Random survival forests. The Annals of Applied Statistics. 2008;**2**:841-860. DOI: 10.1214/08-AOAS169
- [35] Binder H, Schumacher M. Allowing for mandatory covariates in boosting estimation of sparse high-dimensional survival models. BMC Bioinformatics. 2008;**9**:1-10. DOI: 10.1186/1471-2105-9-14
- [36] Sonabend REB. A theoretical and methodological framework for machine learning in survival analysis: Enabling transparent and accessible predictive modelling on right-censored time-toevent data [PhD]. London: University College London (UCL); 2021
- [37] Miot HA. Análise de sobrevivência em estudos clínicos e experimentais. Jornal Vascular Brasileiro. 2017;**16**(4):267-269. DOI: 10.1590/1677-5449.001604
- [38] Marques C, Lise CC, de Lima VA, Daltoé MLM. Survival analysis and cut-off point to estimate the shelf life of refrigerated fish burgers. Food Science and Technology. 2020;**40**(1):171-177. DOI: 10.1590/fst.36918
- [39] Barbin DF, ElMasry G, Sun DW, Allen P. Predicting quality and sensory attributes of pork using near-infrared hyperspectral imaging. Analytica Chimica Acta. 2012;**719**:30-42
- [40] Cheng JH, Sun DW. Rapid and non-invasive detection of fish microbial spoilage by visible and near-infrared hyperspectral imaging and multivariate analysis. LWT - Food Science and Technology. 2015;**62**(2):1060-1068

Edited by Alice Vilela

Sensory analysis is a fundamental discipline in food science, essential for product development, quality control, and consumer research. It provides a structured scientific framework for translating subjective sensory perceptions, such as taste, aroma, and texture, into objective, measurable data. Traditionally, sensory evaluation has relied on descriptive analysis, discrimination tests, and affective tests to assess product attributes and consumer preferences. Descriptive analysis, conducted by trained panels, quantifies sensory characteristics, while affective tests evaluate consumer liking and acceptance. Recent advances have expanded sensory analysis to include emotional and psychological dimensions of food perception. Through physiological and biometric measures such as facial expression recognition, heart rate monitoring, and eye tracking, researchers can capture implicit emotional responses during food consumption. This emerging field, known as emo-sensory research, bridges sensory science and affective psychology, emphasizing the role of emotions in shaping consumer choice, satisfaction, and loyalty. Tools like FaceReader® and EEG-based analyses allow for the objective mapping of emotional reactions to food experiences. Artificial intelligence (AI) has further transformed sensory science by introducing powerful tools for data modeling and prediction. Machine learning algorithms analyze complex sensory and consumer datasets to detect patterns, forecast preferences, and optimize formulations. The integration of sensory science, emo-sensory approaches, and AI opens new possibilities for understanding human–food interactions. Future developments will likely emphasize hybrid human–AI sensory systems, ethical data handling, and standardized methodologies, leading to more personalized, emotionally engaging, and sustainable food innovations.

*Maria Rosário Bronze,
Food Science and Nutrition Series Editor*

Published in London, UK

© 2026 IntechOpen
© Servet Turan / iStock

IntechOpen

ISSN 2977-8174

ISBN 978-1-83635-379-9

