

## HIGHLIGHTS

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- A sensory reverse engineering framework was developed for food optimization.
- The framework created a vegan mousse using aquafaba and apple pomace.
- The optimized formulation closely replicated the sensory qualities of traditional chocolate mousse.
- In this case study, this method enabled efficient development of a sustainable food product.

# Sensory reverse engineering: a framework for sustainable product development used on vegan chocolate mousse

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## Abstract

This study presents a sensory reverse engineering framework designed to optimize food formulations by integrating consumer sensory preferences early in the development process. The framework was applied to the development of a vegan chocolate mousse, a product that meets growing consumer demand for sustainable, plant-based alternatives. The challenge of replacing eggs, which provide critical texture and aeration in traditional mousses, was met with aquafaba (chickpea cooking water) and apple pomace, a by-product of apple processing. While these ingredients offer sustainability benefits, they present sensory challenges such as bitterness and textural variation that require careful formulation.

The framework used Design of Experiments and external preference mapping to systematically optimize the ingredient proportions. Key factors, including margarine, hazelnut milk, and sugar were evaluated for their impact on sensory attributes such as texture, flavor, and appearance. Sensory profiling was conducted with trained panelists, while consumer hedonic testing with 94 participants provided insight into overall product acceptability.

Multi-objective optimization identified the ideal formulation: the optimal vegan mousse formulation achieved a desirable balance of sweetness, texture, and flavor while closely mimicking the sensory qualities of traditional mousse. The final product demonstrated that plant-based ingredients can replicate the sensory experience of egg-based mousses and promote the use of by-products.

In conclusion, the sensory reverse engineering framework provides a robust, consumer-driven approach to food product development. By incorporating consumer feedback into the early stages of formulation, the framework reduces the risks associated with traditional product development, resulting in products that are better aligned with market expectations.

**Key words:** Sensory reverse engineering, vegan chocolate mousse, preference mapping, plant-based products, design of experiments, sensory optimization.

## 38 **Highlights**

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- 40 • The framework created a vegan mousse using aquafaba and apple pomace.
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- 42 chocolate mousse.
- 43 • In this case study, this method enabled efficient development of a sustainable
- 44 food product.

## 45 **1. Introduction**

### 46 **1.1 Background and Justification**

47 The food industry is a dynamic and highly competitive sector, where new product  
48 development is essential to maintain market relevance and meet evolving consumer  
49 demands. However, the innovation process in food product development is fraught with  
50 challenges, as evidenced by the alarmingly high failure rates of new product launches.  
51 According to a literature review, 30-40% of new products fail within their first year on  
52 the market (Rutkowski, 2022). These statistics underscore the inherent difficulties in  
53 creating products that not only meet technical and safety standards but also resonate with  
54 consumer preferences and stand out in a crowded marketplace.

55  
56 According to Earle et al. (2001), there are six types of product development projects:  
57 product cost reduction, product repositioning, product improvement, product line  
58 extension, new product lines, and “new-to-the-world” products.

59  
60 Consumer involvement is a critical factor in the development of new food products to  
61 ensure alignment between product formulations and consumer preferences. However,  
62 not all companies involve consumers in their development processes and there are  
63 significant disparities based on company size and available resources. In fact, less than  
64 50% of the companies studied by Horvat et al. (2019) involve customers in product design.  
65 Large companies are more likely to engage consumers through methods such as focus  
66 groups, surveys, sensory testing, and concept testing. In contrast, small companies often  
67 rely on intuition due to financial or organizational constraints, which limits their ability  
68 to capture accurate consumer insights.

69  
70 This gap in consumer involvement is particularly concerning during critical stages, such  
71 as concept testing or sensory evaluations. The lack of robust consumer testing can lead to  
72 a misalignment between the product and market expectations, increasing the risk of  
73 failure, especially for innovative or “new-to-the-world” products. Moreover, companies  
74 that depend solely on passive data collection methods, such as internet research or

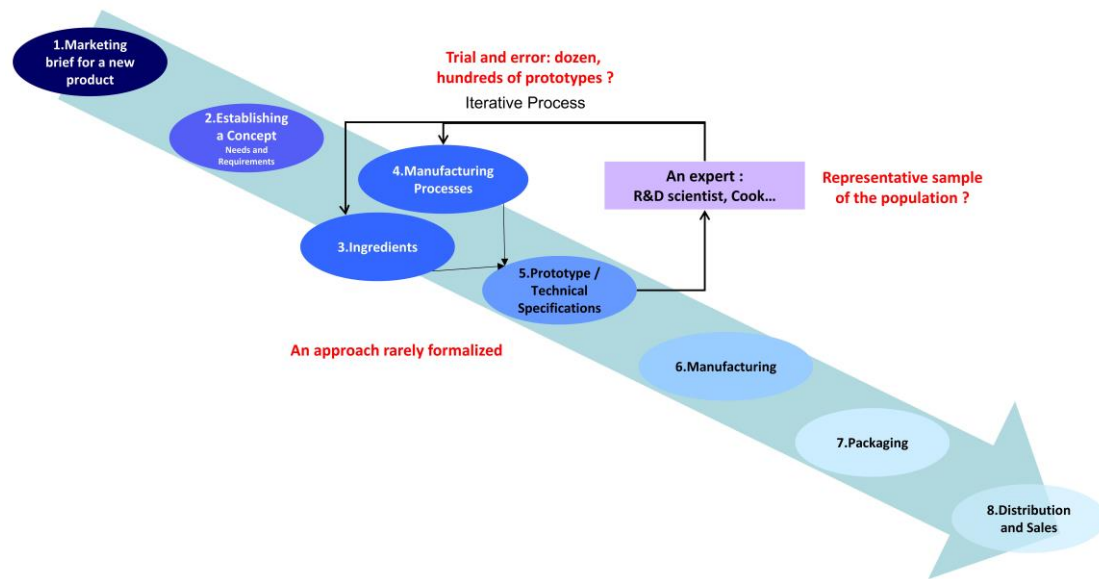
75 secondary sources, may struggle to uncover latent consumer needs and innovation  
76 opportunities (Horvat et al., 2019).

77

78 For these companies, one of the critical challenges in product development is aligning  
79 product attributes with consumer expectations. Traditional approaches to product design  
80 often rely on a linear process that begins with a marketing brief, followed by the concept  
81 formulation, ingredient selection, prototyping, and eventually, manufacturing and  
82 distribution (Earle et al., 2001) (Figure 1):

- 83 1. Marketing brief for a new product: This is the first step in which the idea for the  
84 product is generated. It involves understanding market needs, consumer  
85 demands, and potential opportunities.
- 86 2. Concept creation: Based on the marketing brief, a concept is established. This step  
87 involves defining the product's needs and requirements, including target  
88 consumers, product features, and benefits.
- 89 3. Ingredients: Once the concept is established, the next step is to determine the  
90 ingredients or raw materials required to make the product. This is done under  
91 various constraints such as nutritional, toxicological, technical, and financial  
92 considerations.
- 93 4. Manufacturing processes: With the ingredients identified, the manufacturing  
94 process is designed. This step outlines how the product will be produced on a  
95 technical level, including the methods and technologies to be used.
- 96 5. Prototype/technical specifications: A prototype is created based on the  
97 established concept and manufacturing processes. This prototype includes  
98 detailed technical specifications to ensure that the product meets all the  
99 requirements prior to full-scale production.
- 100 6. Manufacturing: After the prototype is approved, the product enters the  
101 manufacturing phase. This involves the actual production of the product on a  
102 larger scale.
- 103 7. Packaging: After manufacturing, the product is packaged. This step involves  
104 designing and selecting appropriate packaging materials and methods to protect  
105 the product and make it appealing to consumers.
- 106 8. Distribution and sales: The final step is to bring the product to the market. This  
107 involves distributing the product to retailers and making it available to  
108 consumers.

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111 **Figure 1 : An example of “traditional” approach of new product design, adapted from Earle et al.,**  
112 **2001, showing the different steps and their potential issues.**

113  
114 While methodical, this expert-driven approach relies heavily on insights from R&D  
115 scientists, chefs, or developers. Although these experts have valuable knowledge and  
116 experience, their perspectives may not always fully represent the preferences and desires  
117 of the target consumer base (Horvat et al., 2019). As a result, products developed using  
118 traditional methods may only achieve local optimal solutions that meet specific criteria  
119 but fail to achieve broader market acceptance. Moreover, the iterative nature of  
120 traditional product development often involves multiple cycles of trial and error, which  
121 can be time-consuming and costly. This process typically lacks structured consumer input  
122 in the early stages of product design, leading to missed opportunities for optimizing  
123 sensory attributes that are critical to consumer satisfaction (Earle et al., 2001). In the  
124 context of the food industry, where sensory appeal - such as taste, flavor, texture, and  
125 aroma - is a key determinant of product success, this gap between expert assumptions  
126 and consumer preferences can be particularly detrimental.

## 127 1.2 Problem Statement and Objectives

128 In response to the limitations of traditional product development approaches, there is a  
129 growing recognition of the need to integrate consumer preferences into the design  
130 process from the outset. This integration is especially important in the current era, where  
131 consumer demand for sustainable, health-conscious, and ethically produced food  
132 products is increasing. The challenge lies not only in developing products that meet these  
133 criteria but also in ensuring that they deliver the sensory experience consumers expect  
134 and enjoy (Horvat et al., 2019). The objective of this study is to introduce and validate a  
135 sensory reverse engineering framework that facilitates the development of food products  
136 tailored to consumer preferences. This framework is designed to systematically  
137 incorporate consumer feedback into the formulation and optimization process, thereby  
138 bridging the gap between technical feasibility and market acceptance. The framework is  
139 applied in a case study on the development of a vegan chocolate mousse—a product

140 requiring the replacement of eggs with plant-based alternative ingredients that are both  
141 sustainable and sensorially acceptable.

### 142 1.3 The case study

143 Currently, consumer interest in sustainable food is growing, with trends favoring ‘more  
144 natural’ or less processed ingredients and plant-based alternatives over animal-derived  
145 ingredients (Alae-Carew et al., 2022; Aschemann-Witzel et al., 2021). Moreover,  
146 increasing awareness of biomass losses from plant production to consumption is driving  
147 research on byproduct valorization. Indeed, only 25% of the harvested agricultural  
148 biomass is consumed as food (Alexander et al., 2017). Byproduct composition is of  
149 interest for various applications: in food for their nutritional qualities (fiber, proteins), as  
150 emulsifier due to its amphiphilic compounds (Hollestelle et al., 2024; Ralla et al., 2018),  
151 as antioxidant agent (thanks to polyphenols, for example) (Dzah et al., 2020; Lu & Foo,  
152 1997), as a natural coloring agent due to its pigments (Sharma et al., 2021), as film-  
153 forming agent thanks to biopolymers (cellulose or pectin among others) (Santhosh et al.,  
154 2021), or for bioenergy due to its sugar content (Panwar et al., 2021). Many studies focus  
155 on purified molecules extracted from byproducts to enable ingredient standardization  
156 and control over color and smell, which can interfere with consumer acceptability.  
157 However, this process requires solvents and energy, and a large portion of the material  
158 remains unutilized.

159 Industries have recognized these evolving consumers expectations leading to the  
160 emergence of new product categories. However, it necessitates the replacement of  
161 controversial ingredients, generally affecting the sensory properties of well-known  
162 products, which may lead to lower consumer appreciation and ultimately to a commercial  
163 failure. While consumers are increasingly aware of environmental and nutritional issues,  
164 their expectations remain high, and they are often unwilling to compromise on taste or  
165 texture (Fiorentini et al., 2020).

166

167 The case study presented in this research focuses on the development of a vegan  
168 chocolate mousse, a product that presents significant challenges due to the need to  
169 replace eggs with plant-based alternatives. Eggs play a crucial role in traditional mousse  
170 recipes by providing structure, aeration, and stability. Replacing eggs with aquafaba (the  
171 water in which chickpeas have been cooked), while achieving similar sensory properties,  
172 is a complex task that requires a careful balance of ingredients. The in-store audits  
173 revealed that the most common flavor for mousses in France is chocolate. Thus, the focus  
174 of this study was on vegan chocolate mousses.

175

176 Previous research on egg substitutes in food products has highlighted the potential of  
177 various plant-based alternatives, with aquafaba emerging as a particularly promising  
178 option. Aquafaba's ability to mimic the foaming and emulsifying properties of egg whites  
179 has made it a popular choice for vegan and allergen-free food manufacturers (Buhl et al.,  
180 2019; Tufaro & Cappa, 2023). However, its application in industrial settings is challenged  
181 by issues of consistency, stability, and flavor, particularly in products that require a

182 delicate balance of texture, flavor and taste, such as mousse. Similarly, the use of apple  
183 pomace—a by-product of apple processing—has been explored as a functional ingredient  
184 in food products (Hollestelle et al., 2024; Huc-Mathis et al., 2019; Lu et al., 2020).  
185 However, its inherent bitterness and potential impact on flavor profiles necessitate  
186 careful consideration in product design, especially when targeting a broad consumer base  
187 (Lu & Foo, 1997). While these studies provide valuable insights into the functional  
188 properties of aquafaba and apple pomace, they often fail to address the complex  
189 interactions between ingredients and their combined impact on consumer perception.

190

191 This gap in literature underscores the need for a more holistic approach to product  
192 development—one that integrates sensory science, consumer research, and advanced  
193 experimental design techniques. The sensory reverse engineering framework proposed  
194 in this study aims to address this gap by combining the strengths of traditional sensory  
195 analysis with modern data-driven methodologies. By leveraging techniques such as  
196 design of experiments (DoE), external preference mapping, and multi-objective  
197 optimization, this framework provides a structured pathway for developing products that  
198 are both technically sound and highly appealing to consumers.

## 199 **2. Materials and Methods**

### 200 **2.1 Sensory Reverse Engineering Framework**

201 The sensory reverse engineering framework developed in this research is a systematic  
202 approach designed to optimize food product formulations based on consumer sensory  
203 preferences. The framework consists of several key stages, each of which plays a critical  
204 role in ensuring that the final product meets both technical and consumer criteria. We  
205 first describe the generic stages of the sensory reverse engineering framework (Figure 2).  
206 The specific case study on vegan chocolate mousse is then used to illustrate its  
207 implementation in the following sections.

208

#### 209 Stage 1: Identification of Key Factors

210 The first step in the framework involves identifying key factors that influence the sensory  
211 characteristics of the product. These factors may include ingredients, processing  
212 methods, and environmental conditions during production. The selection of these factors  
213 is guided by a combination of a review of existing products on the market, expert  
214 knowledge and eventually a preliminary consumer study.

215

#### 216 Stage 2: Design of Experiments

217 Once the key factors are identified, a design of experiments approach is employed to  
218 systematically explore the interactions among them using, response surface design,  
219 mixture design, optimal design. DoE is a powerful statistical tool that allows researchers

220 to model the effects of multiple variables simultaneously, thereby providing insights into  
221 the optimal combination of ingredients and processing conditions (Becerra & Goos, 2023;  
222 Dooley et al., 2012; Reyniers et al., 2022).

223

### 224 Stage 3: Sensory Profiling and Data Collection

225 The next stage involves the collection of sensory data from trained panelists. Sensory  
226 profiling is conducted to evaluate the products across multiple sensory dimensions,  
227 including appearance, aroma, flavor, taste and texture. The collected data serve as the  
228 basis for response surface modeling to predict sensory scores with DoE factors.

229

### 230 Stage 4: Consumer Testing and Hedonic Evaluation

231 Consumer testing is conducted to gather data on consumer preferences and acceptance  
232 of the product. Hedonic evaluation, where consumers rate their liking of the product on a  
233 scale, is a key component of this stage. The data from consumer testing are then used to  
234 create external preference maps, which help identify sensory scores that maximize  
235 consumer acceptance.

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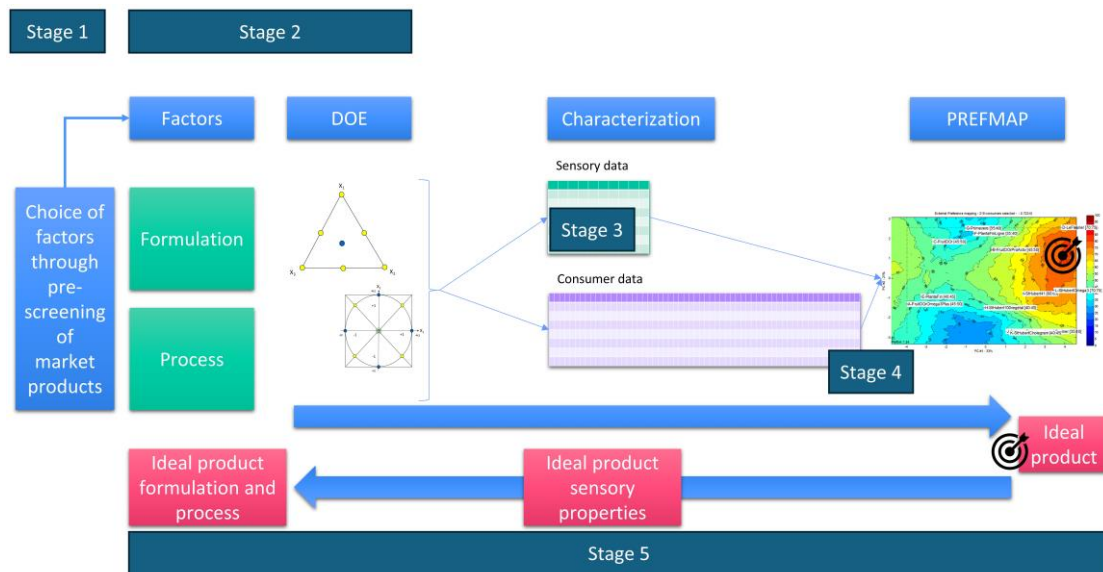
### 237 Stage 5: Multi-Objective Optimization

238 The final stage of the framework applies multi-objective optimization techniques to  
239 identify the ideal formulation that balances the various sensory attributes desired by  
240 consumers.

241 The sensory data collected for each formulation are used to fit response surface models  
242 (RSM) for the main sensory attributes. These models allow for the estimation of expected  
243 sensory responses for any combination of ingredients within the design space. The  
244 regression model structure depends on the type of DoE used (Cornell, 2002). RSMs are  
245 then used to visualize the individual and combined effects of ingredients on sensory  
246 responses, and to identify combinations that achieve targeted sensory profiles. These  
247 models form the basis for subsequent optimization and preference mapping steps.

248 Therefore, using RSMs, this stage predicts sensory outcomes based on the ingredient  
249 combinations, ensuring that the final product is both technically feasible and highly  
250 appealing to consumers.

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**Figure 2: Sensory reverse engineering framework showing the different stages of the new product development.**

256 In this case study on vegan chocolate mousse, the primary objective of the formulation  
257 process was to create a mousse that closely replicated the sensory properties of a  
258 traditional egg-based mousse while being entirely plant-based.

## 259 2.2 Factors & Experimental Design (Stages 1 and 2)

260 In stage 1, five food experts, two in physicochemical analysis and three in sensory science,  
261 identified functionally relevant ingredients. First, a review of existing products was  
262 conducted through in-store audits at major French retailers. This included a systematic  
263 analysis of ingredient lists for each mousse product, aiming to identify the nature and  
264 functional role of each component in the overall formulation. Second, a preliminary  
265 consumer survey with participants (n = 16, gender-balanced, aged between 22 and 25  
266 years) was conducted to assess expectations and preferences related to vegan chocolate  
267 desserts.

268  
269 For the recipe, aquafaba chickpea (Cora®, France) and apple pomace (VITACEL® CS5  
270 APPLE, JRS Rettenmaier, Germany) were chosen for texture and stability. Chocolate  
271 (Nestlé Dessert® Noir Absolu, Switzerland) and cacao (Van Houten®, Netherlands) were  
272 chosen for the chocolate flavor.

273 Aquafaba and apple pomace relative percentages were fixed based on preliminary trials  
274 to optimize the foaming and structuring capacity. Varying these ingredients in the main  
275 experimental design would have compromised mousse stability.

276  
277 Then, the formulation of different mousses over a wide range of design factors allowed us  
278 to identify several key ingredients for texture, taste, flavor and aroma: sugar (Daddy®,

1 279 France), hazelnut milk (Bjorg®, France) and margarine (Saint Hubert®, France). Then,  
2 280 two criteria were considered to choose the maximum content of these ingredients: the  
3 281 formulation process and the nutritional aspect, ensuring a stable chocolate mousse  
4 282 without higher sugar or fat contents than commercial references, respectively between  
5 283 16% and 28% for sugar and between 5% and 32% for fat.

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9 285 In stage 2, four ingredients were fixed (corresponding to 62.5% w/w of the formula):  
10 286 aquafaba chickpea (28.85%), apple pomace (3.6%), chocolate (28.85%) and cacao  
11 287 (1.2%). The remaining 37.5% were considered as a mixture of sugar, hazelnut milk and  
12 288 margarine. Therefore, the factors considered in this design were the proportions of  
13 289 margarine, hazelnut milk, and sugar.

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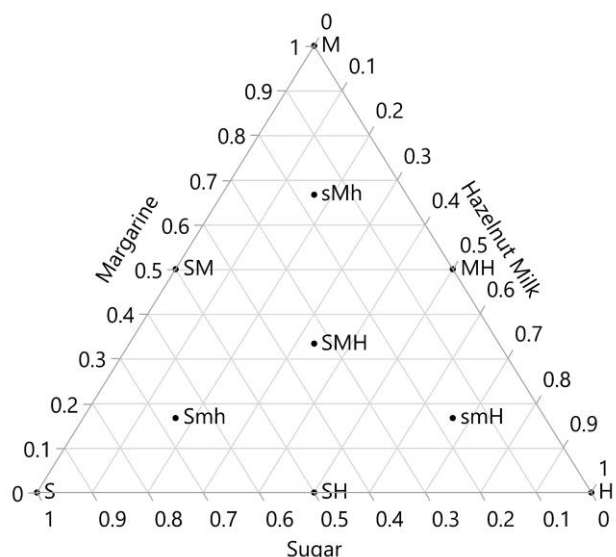
18  
19 291 An augmented simplex centroid design was chosen for its balanced exploration of the  
20 292 factor space, ensuring that all possible ingredient combinations were tested. The design  
21 293 was augmented with axial points to validate the model and explore finer variations in  
22 294 ingredient ratios (Cornell, 2002). The simplex centroid design is mathematically justified  
23 295 by its ability to model the interaction effects between multiple ingredients, which is  
24 296 critical for understanding how changes in one ingredient affect the overall sensory profile.  
25 297 The design is also efficient, requiring fewer experimental runs than a full factorial design  
26 298 while still providing comprehensive data.

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32 300 The implementation of the DoE involved preparing 10 mousses (one for each recipe)  
33 301 according to the design matrix (Figure 3). The use of axial points in the design allowed for  
34 302 the testing of ingredient combinations that were not on the original simplex, providing  
35 303 additional validation for the models developed in later stages.

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Recipe	Sugar (S)	Margarine (M)	Hazelnut Milk (H)
S	1	0	0
M	0	1	0
H	0	0	1
SM	1/2	1/2	0
SH	1/2	0	1/2
MH	0	1/2	1/2
SMH	1/3	1/3	1/3
Smh	2/3	1/6	1/6
sMh	1/6	2/3	1/6
smH	1/6	1/6	2/3

Figure 3: Mixture design (augmented simplex centroid) - ternary plot for product locations and formulations for the 10 mousses (on left) and composition ratios table (on right): three single ingredients, three binary blends and four tertiary blends.

S, M, H stand respectively for sugar, margarine and hazelnut milk. The code of the product is based on the percentage of each ingredient: when a letter is in capital, the corresponding ingredient has a higher ratio for this recipe. For example, S contains only sugar; Smh contains sugar with a higher ratio (2/3) and contains also margarine and hazelnut milk with equal and lower ratio (1/6).

313

### 314 Samples preparation

315 Aquafaba chickpea was whipped using a food processor (KitchenAid®, United States) at  
 316 maximum speed (10) during 4 minutes at room temperature, then apple pomace was  
 317 sifted and added in the aquafaba foam. They were mixed at maximum speed during 20 s  
 318 and the bowl sides were scrapped using a spatula to homogenize.

319 For most mousses (except recipes S and Smh), once the chocolate melted in a water-bath  
 320 with sugar and hazelnut milk (if present in the recipe), it was added to the margarine and  
 321 cacao and whisked. Aquafaba was then gently incorporated using a spatula.

322 For recipes S and Smh, the process had to be slightly adjusted because they contained a  
 323 large amount of sugar. For Smh, once the chocolate was melted in a water-bath with the  
 324 hazelnut milk, the sugar was added off the heat. This mixture was added to the margarine  
 325 and cacao. After cooling for 5 minutes, 1/3 of the aquafaba was added and vigorously  
 326 whisked to obtain a less thick paste. The remaining aquafaba was then gently  
 327 incorporated using a spatula. For recipe S, the process was the same as Smh, excluding  
 328 hazelnut milk and margarine. Even if these changes could have a relative impact on the  
 329 final sensory properties of the mousses, the choice was to explore the whole range of  
 330 percentage of the three ingredients (from 0% to 100%) to avoid obtaining a local  
 331 optimum.

332 After dividing each mousse into individual cups with lid, the samples were stored at 4°C  
 333 for a couple of hours.

### 334 2.3 Characterization: Sensory Profiling (Stage 3)

335 A sensory profile, adapted from QDA®, was conducted over five sessions by 11 trained  
336 assessors (Meilgaard et al., 2006).

337 The panelists evaluated the mousses on seven sensory dimensions: appearance, odor,  
338 texture with a spoon, flavor, taste, texture during tasting, and texture after tasting. The  
339 first step was to establish a common language for describing chocolate mousses.  
340 Assessors have generated attributes individually on the whole set of products (n=10) and  
341 they reduced the list in three sessions: (i) by a discussion among all the assessors, (ii) by  
342 answering to the question “is the attribute applied to the mousse?” for each mousse and  
343 each attribute, (iii) by scoring each mousse between “0” and “5” for each attribute  
344 (International Organization for Standardization, 1994). This allowed the selection of  
345 discriminant and non-redundant terms. Finally, two sessions were devoted to evaluating  
346 the intensity of the perceived sensations for each product and attribute. The 10 chocolate  
347 mousses, coded with three-digit numbers, were presented one by one in a sequential  
348 monadic design, following a Latin square arrangement. Each assessor scored the mousses  
349 with a decimal score between “0” and “10” (International Organization for  
350 Standardization, 2003) using Google Forms.

351

#### 352 Statistical analysis

353 To evaluate the reliability of the sensory data: a two-way analysis of variance (ANOVA)  
354 (product, panelist and interaction) was carried out to determine which attributes could  
355 differentiate the products. Products and panelists were estimated as fixed effects.

356 To illustrate the results, Principal Component Analysis (PCA) was performed on the  
357 average scores of the sensory profile to provide a multivariate graphical representation  
358 of the products.

### 359 2.4 Characterization: Hedonic Tests (Stage 4)

360 Hedonic testing was conducted with 94 participants, mainly students from  
361 AgroParisTech. The demographic profile of the consumer panel included 68% females,  
362 and 84% individuals aged between 18 and 25 years.

363 Consumers rated their liking of the 10 mousse samples on a numerical scale from “0” to  
364 “10”. The anchors of the scale were labelled as follows “0”: “I do not like” and “10”: “I like  
365 a lot”. The study was designed using a Latin square design for a complete and balanced  
366 design.

367

#### 368 Statistical analysis

369 The hedonic data were analyzed using two-way ANOVA (product, consumer) to  
370 determine the significance of the differences between the different mousse formulations.  
371 Products and consumers were estimated as fixed effects. Post-hoc tests, with Tukey's HSD,

372 were used to identify specific pairs of formulations that differed significantly in terms of  
373 consumer liking. The results of the hedonic test were crucial in identifying the most and  
374 least liked formulations, which informed the final optimization process.

## 375 **2.5 Fitting models (Stage 5)**

### 376 **From DoE factors to sensory attributes**

377 Response surface models for mixture DoE were developed to predict sensory scores  
378 (dependent variables) with the ingredient proportions (independent factors) and to  
379 identify which sensory attributes were influenced by which factors. Polynomial  
380 regression models were fitted using the second-order Scheffe model appropriate for  
381 mixture designs (without the intercept, with all the linear main-effect terms, without the  
382 quadratic terms, with all the 2<sup>nd</sup> order cross terms) (Becerra & Goos, 2023).

383

### 384 **From sensory attributes to consumers scores**

385 The external preference mapping was performed with quadratic model. In addition to  
386 capturing non-linear relationships between individual attributes and liking, the quadratic  
387 model also allows for the representation of more complex preference structures in the  
388 sensory space. For instance, it could account for bimodal preference distributions, where  
389 a consumer could have two distinct zones of high liking in opposite regions of the  
390 sensorial map — a behavior that could not be modeled by simpler models such as  
391 vectorial, circular and elliptic (Danzart & Heyd, 1996). The identification of the sensory  
392 scores of the optimal products on the preference mapping was obtained by the barycenter  
393 method (Blumenthal, 2004; Masson et al., 2016).

394

### 395 **From ideal sensory scores to DoE Factors**

396 The JMP profiler (SAS Institute Inc., 2021) was used. The profiler facilitated visual  
397 exploration and optimization of responses based on different factor levels. In this context  
398 of mixture designs, the profiler displayed how modifications of ingredient proportions  
399 affected the sensory scores. One of the key features of the profiler was used: the  
400 desirability function, to specify objectives for each response (Derringer & Suich, 1980). In  
401 this framework, each attribute had its own objective: the sensory score of the optimal  
402 product obtained after the preference mapping.

403 Combining these desirability functions, an overall desirability score allowed the  
404 identification of the optimal settings for ingredient proportions. This was particularly  
405 useful for balancing trade-offs between competing responses, ultimately guiding  
406 decision-making toward the most desirable outcomes. In this case, changing the  
407 proportion of one ingredient (and therefore at least one other) was considered for all the  
408 sensory attributes at one.

409

410 Preference mapping was conducted using MATLAB version: 9.13.0 (R2022b), Natick,  
 411 Massachusetts: The MathWorks Inc. All other analyses were performed using JMP®,  
 412 version 16. SAS Institute Inc., Cary, NC, 1989–2023.

### 413 3. Results

#### 414 3.1 Sensory Data Analysis

415 Initially, they generated over 280 sensory terms to describe the mousses. These terms  
 416 were then reduced to 14 significant attributes through a combination of statistical  
 417 analysis and consensus. The final attributes included descriptors such as airy texture,  
 418 sweet taste, bitter aftertaste and buttery flavor (Table 1). Definitions and evaluation  
 419 protocols were established by the panelists.

420

421 **Table 1 : Selected sensory attributes by 11 panelists after three sessions (one for generation and two**  
 422 **for selection of attributes).**

Step	Before tasting			During tasting			After tasting
Category	Aspect	Smell	Texture with spoon	Taste	Flavor	Texture	Texture
Attribute	-Dark	-Butter	-Resistant	-Bitter	-Chocolate	-Dense	-Film
	-Grainy	-Chocolate	to spoon	-Sweet	-Apple		
			-Elastic		-Butter		
			-Airy				

423

424 The significance of each term was evaluated, and non-significant terms were removed  
 425 through stepwise backward selection to improve model parsimony. The results of the  
 426 ANOVA were satisfactory as the Product effect was significant for all the attributes (Table  
 427 2). The interaction was significant for four attributes, but its F-ratio was low according to  
 428 the F-ratio of the Product effect.

429

430

Table 2 : ANOVA effect tests after stepwise backward selection.

431 Results from analysis of variance for 14 sensory attributes (rows) showing F-Ratios, Prob > F and  
 432 significance levels for fixed effects Product, Panelist and their interaction (columns).

Attribute	Product Effect			Panelist Effect			Product x Panelist Interaction		
	F Ratio	Prob > F	Significance level	F Ratio	Prob > F	Significance level	F Ratio	Prob > F	Significance level
appearance: dark	19.4	0.000	***	9.3	0.000	***			
appearance: grainy	4.3	0.000	***	5.2	0.000	***			
odor: buttery	6.9	0.000	***	6.8	0.000	***			
odor: chocolate	2.4	0.009	**	7.1	0.000	***			
texture with spoon: airy	4.1	0.000	***	3.2	0.001	***			
texture with spoon: elastic	7.3	0.000	***	7.9	0.000	***			
texture with spoon: spoon resistance	38.2	0.000	***	3.5	0.000	***			
taste: bitter	20.2	0.000	***	10.3	0.000	***			
taste: sweet	37.4	0.000	***	5.9	0.000	***	1.5	0.013	*
flavor: apple	3.5	0.000	***	10.9	0.000	***			
flavor: buttery	14.4	0.000	***	5.1	0.000	***	1.6	0.005	**
flavor: chocolate	7.4	0.000	***	12.4	0.000	***	1.4	0.034	*
texture during tasting: dense	25.4	0.000	***	4.3	0.000	***			
texture after tasting: film	5.5	0.000	***	13.7	0.000	***	1.8	0.001	**

433 Note: P-levels indicated as: \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001.

434

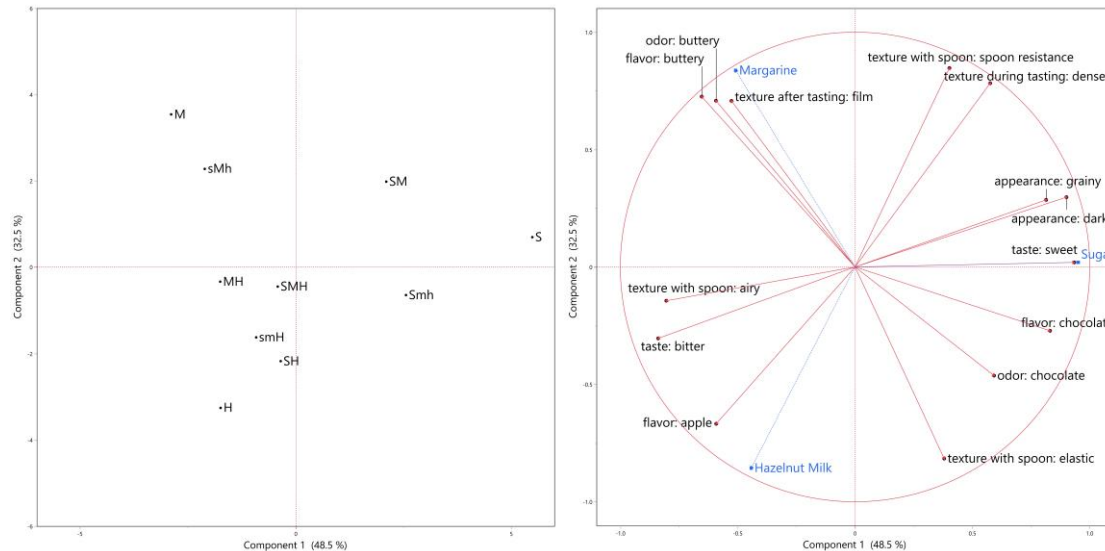
435 The final lexicon used in this study represented a reduced subset of the initial pool of  
 436 sensory attributes generated by the panel. Some attributes that could have been relevant  
 437 for a broader range of products in this category—such as creaminess or smoothness—  
 438 were not retained, either because they were not elicited within the specific sensory space  
 439 explored, or because they were considered by the panel to be redundant with other highly  
 440 correlated terms. This consolidation process, while necessary for operational clarity, may  
 441 have led to the exclusion of descriptors that could be important in a wider context.

442

443 The sensory data collected from the trained panelists were subjected to PCA to identify  
 444 patterns and relationships among the different formulations of the vegan chocolate  
 445 mousses. The PCA plot showed that the first two principal components (PC1 and PC2)

446 explained 81% of the total variance in the sensory data. PC1 was primarily associated  
 447 with the sweetness and the chocolate flavor of the mousses, while PC2 was linked to the  
 448 bitterness, the apple flavor, and the texture after tasting (Figure 4).

449



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**Figure 4 : PCA showing descriptive analysis product scores and variable loadings for the 10 mousse samples on the first two dimensions, accounting for 81% of the variability. Ingredient ratios are represented as supplementary variables (in blue).**

454

455 The separation between the different formulations was evident in the PCA plot, with  
 456 formulations high in sugar positioned on the positive side of PC1 (S, Smh and SM),  
 457 reflecting their association with sensory attributes such as sweetness. In contrast,  
 458 formulations with higher levels of hazelnut milk (H) or margarine (M, sMh) were located  
 459 on the negative side of PC2, correlating with bitterness and apple flavor. In fact, the initial  
 460 experimental design (Figure 3) was quite visible on the PCA. The initial points moved,  
 461 some more than others. For example, SMH was not the barycenter of the triangle anymore.  
 462 MH, SM and SH were not in the middle of their respective segments (respectively at equal  
 463 distance of M and H, S and M, S and H). This was due to sensory perceptions and their  
 464 interactions.

465

466 There was an opposition between the taste “sweet” on one hand, and the taste “bitter” and  
 467 the flavor “apple” on the other hand. Product S was the sweeter one. Furthermore, the  
 468 lower the sugar content, the more bitter the product was. Increasing margarine and sugar  
 469 tended to raise the density and resistance of the texture, as there was less milk. And the  
 470 less sugar the products had, the “airier” was the texture. But as the margarine enhanced  
 471 the texture, it also added buttery aspects that masked the chocolate flavor.

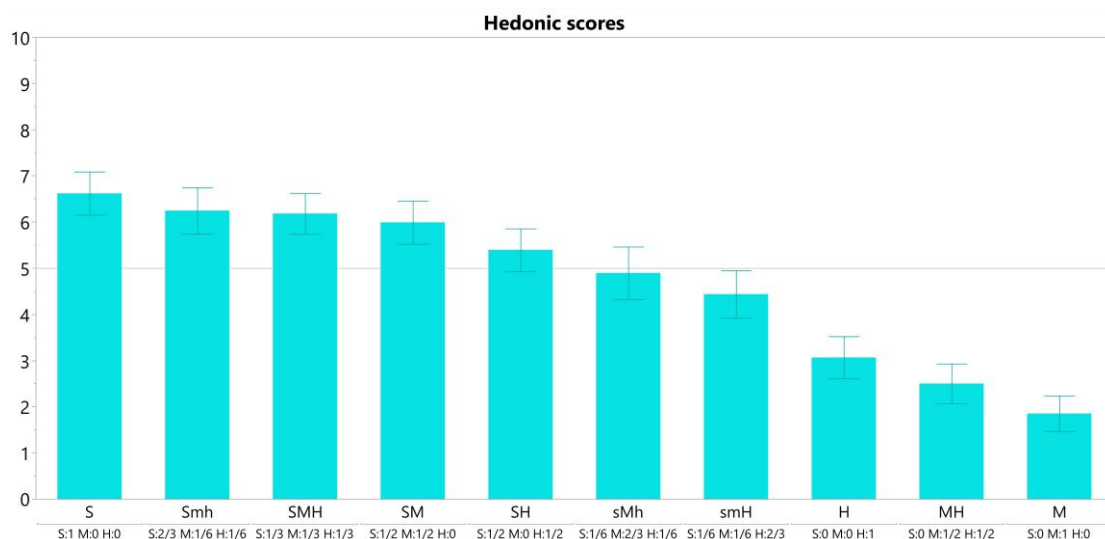
472 The formulations with less sugar and more hazelnut milk were characterized by their  
 473 bitterness and apple flavor (even if the percentage of apple pomace is fixed).

474 **3.2 Hedonic Scores analysis**

475 Overall, the scores were mid-range. The range of the mean scores was from 1.85 to 6.62  
 476 out of 10, indicating that some products were not appreciated whereas some others were  
 477 globally pleasant. For example, the most liked product had scores ranging from 0 to 10  
 478 (Q1 = 5, Median = 7, Q3=9).

480 The ANOVA results revealed significant differences in hedonic scores between  
 481 formulations  $F_{\text{product}}(9, 837)=61.15, p<0.0001$ . Post-hoc comparisons indicated that the  
 482 highest-rated formulation (S) was significantly more liked over all others except one  
 483 (Smh).

485 Sample M, which contained the highest amount of margarine, was the least appreciated  
 486 by consumers (1.85). The samples H and MH had also very poor acceptability  
 487 (respectively 3.06 and 2.50), probably because they did not contain sugar. Then, by  
 488 increasing the sugar content, the scores grew up to 6.62 for the sample S (higher sugar  
 489 content) (Figure 5). Therefore, unsurprisingly, sugar seemed to be the main factor of  
 490 appreciation.



491 **Figure 5 : Mean hedonic scores bar graph showing the liking of consumers for the 10 samples.**  
 492 **The ingredient proportions are detailed below the label of the products S, M H stand respectively for sugar,**  
 493 **margarine and hazelnut milk. Each error bar is constructed using a 95% confidence interval.**

496 A clustering analysis was conducted. As the consumers of the two clusters had the same  
 497 opinion on the least and most liked products and only differed on the “average” products,  
 498 no further details are included in this paper.

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499 **3.3 Fitting models**

500 **From DoE factors to sensory attributes**

501 The RSMs provided a quantitative basis for the final optimization of the mousse  
502 formulation, ensuring that the product met consumer expectations for all key sensory  
503 attributes.

504

505 The  $R^2$  values ranged from 0.77 to 0.99, indicating strong predictive capacity. The range  
506 of p values of the individual ANOVAs ranged from 0.0006 to 0.18, indicating differences  
507 between the models. The bitter taste had the best model, while the chocolate odor had the  
508 worst model (Table 3).

509

510 To identify the optimal settings for the mixture components, the individual models for  
511 each attribute needed to have the same terms, even if one term is not significant for one  
512 attribute. Since all the terms were significant for the attribute airy texture with spoon,  
513 none were removed. The interaction sugar  $\times$  hazelnut milk was significant at the 10%  
514 level for five attributes: two related to appearance, two to texture, and one to taste.

515 Interestingly, the stepwise backward selection for chocolate odor would have retained  
516 only sugar and hazelnut milk as predictors, resulting in a model p-value of 0.03%.

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**Table 3 : Scheffé polynomial models: ANOVA effect tests.**  
Results from analysis of variance for 14 sensory attributes (rows) showing F-Ratios, Prob > F and significance levels for global models and all the terms (columns).

Attribute	Global			Sugar			Hazelnut Milk			Margarine			Sugar *Hazelnut Milk			Sugar *Margarine			Margarine *Hazelnut Milk			
	R <sup>2</sup>	F Ratio	Prob>F	Sig. level	F Ratio	Prob>F	Sig. level	F Ratio	Prob>F	Sig. level	F Ratio	Prob>F	Sig. level	F Ratio	Prob>F	Sig. level	F Ratio	Prob>F	Sig. level	F Ratio	Prob>F	Sig. level
appearance: dark	0.91	7.7	0.036	*	352.5	0.000	***	152.6	0.000	***	164.2	0.000	***	9.4	0.038	*	0.1	0.779	NS	0.0	0.987	NS
appearance: grainy	0.84	4.1	0.098	NS	54.4	0.002	**	12.4	0.024	*	9.6	0.036	*	7.6	0.051	NS	0.0	0.954	NS	0.2	0.694	NS
odor: buttery	0.89	6.3	0.050	NS	18.3	0.013	*	30.2	0.005	**	100.8	0.001	***	1.5	0.294	NS	0.4	0.567	NS	0.2	0.682	NS
odor: chocolate	0.77	2.7	0.183	NS	111.8	0.000	***	81.5	0.001	***	39.0	0.003	**	0.0	0.939	NS	1.3	0.321	NS	3.8	0.124	NS
texture with spoon: airy	0.98	49.1	0.001	**	241.2	0.000	***	713.4	0.000	***	842.2	0.000	***	79.5	0.001	***	8.9	0.041	*	26.0	0.007	**
texture with spoon: elastic	0.85	4.5	0.086	NS	35.5	0.004	**	50.4	0.002	**	2.3	0.202	NS	0.7	0.438	NS	0.0	0.906	NS	0.2	0.672	NS
texture with spoon: spoon resistance	0.94	11.6	0.017	*	195.2	0.000	***	29.5	0.006	**	176.4	0.000	***	0.1	0.751	NS	0.1	0.751	NS	3.2	0.149	NS
taste: bitter	0.99	65.8	0.001	***	19.9	0.011	*	613.8	0.000	***	311.9	0.000	***	6.3	0.066	NS	3.1	0.152	NS	0.2	0.645	NS
taste: sweet	0.99	57.4	0.001	***	461.5	0.000	***	22.8	0.009	**	19.5	0.012	*	0.6	0.483	NS	5.0	0.090	NS	0.3	0.617	NS
flavor: apple	0.86	5.1	0.070	NS	12.8	0.023	*	69.8	0.001	**	29.3	0.006	**	4.1	0.114	NS	0.3	0.615	NS	0.0	0.876	NS
flavor: buttery	0.97	30.1	0.003	**	8.9	0.040	*	30.8	0.005	**	305.8	0.000	***	3.5	0.136	NS	0.5	0.529	NS	0.0	0.940	NS
flavor: chocolate	0.89	6.7	0.045	*	176.2	0.000	***	98.6	0.001	***	48.8	0.002	**	0.1	0.821	NS	6.4	0.065	NS	0.8	0.411	NS
texture during tasting: dense	0.93	11.0	0.019	*	138.3	0.000	***	15.4	0.017	*	90.3	0.001	***	5.9	0.073	NS	0.0	0.873	NS	0.0	0.895	NS
texture after tasting: film	0.86	4.8	0.078	NS	10.0	0.034	*	18.7	0.012	*	80.6	0.001	***	2.0	0.230	NS	1.3	0.314	NS	0.5	0.521	NS

521 Note: P-levels indicated as: NS= p> 0.05, \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001.

522

523 The “spoon resistance” response surface revealed that margarine and sugar significantly  
524 influenced the texture with spoon, with higher levels leading in increased spoon  
525 resistance and a denser texture. The same level of “spoon resistance” could be achieved  
526 with 100% margarine or 100% sugar. This could be useful for maximizing “spoon  
527 resistance” without using sugar (Figure 6 left).

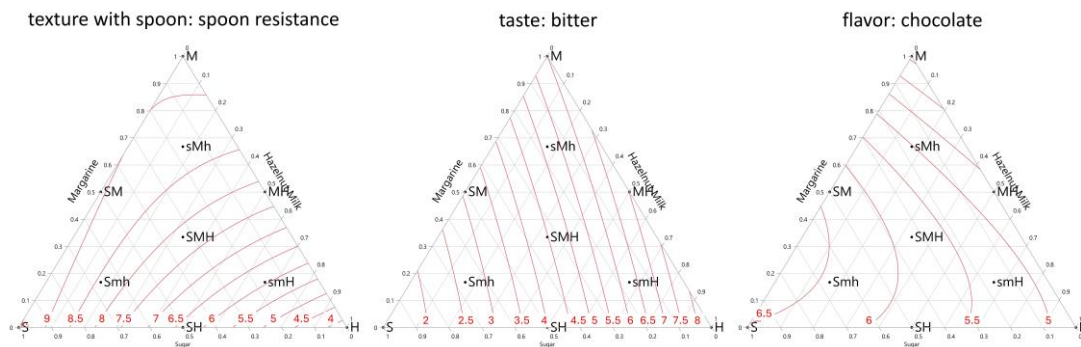
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529 The bitterness was brought by the apple pomace, which was fixed in this study.  
530 Surprisingly, there was a significant product effect for this attribute (Table 2) and the  
531 bitterness model is also significant. The “bitterness” response surface showed a strong  
532 negative correlation with sugar, confirming its contribution to mask the undesirable  
533 bitter notes in the mousse (Figure 6 middle). These findings were similar to those of  
534 Bakke et al. (2018).

535

536 The chocolate flavor response surface demonstrated a positive linear relationship with  
537 sugar content. The model also highlighted the negative impact of apple pomace on  
538 sweetness, as formulations with higher apple pomace content had lower sweetness  
539 scores. The model also indicated that the same level of chocolate flavor can be achieved  
540 with 100% sugar or a mixture of 55% sugar and 45% margarine (Figure 6 right).

541



542  
543 **Figure 6: Representative response surface plots for three sensory attributes: spoon resistance**  
544 **(texture), bitter (taste), and chocolate (flavor).**

545 **The contour lines indicate the predicted mean sensory score for each attribute, as a function of the**  
546 **proportions of sugar, margarine, and hazelnut milk. The values on the contour lines correspond to**  
547 **the intensity levels perceived for the respective attribute.**  
548

549 **Preference Mapping**

550 The external preference mapping analysis provided a visual representation of consumer  
551 preferences in relation to the sensory attributes of the mousse formulations. The  
552 preference map identified a region within the simplex centroid that was most closely  
553 associated with high consumer liking. This area was almost at the center of gravity of the  
554 triangle formed with the full sugar product (S), the 2/3 sugar product (Smh) and the 1/2  
555 sugar-1/2 margarine product (SM). The least preferred areas were near the full-  
556 margarine product (M) and the full-hazelnut milk product (H) (Figure 7).

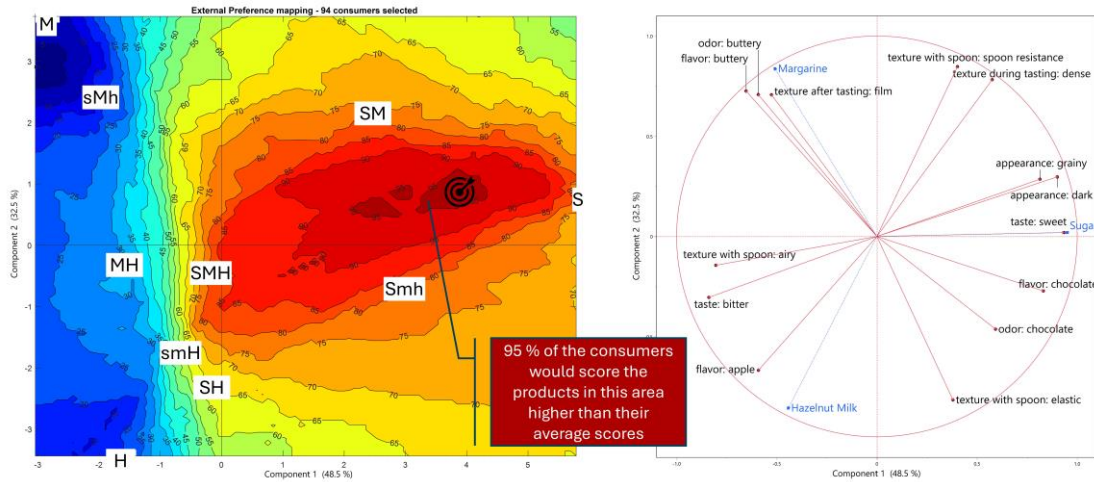
557

558 The levels of  $R^2$  of each individual consumer were sufficient to use the results: from 0.18  
559 to 0.99 with a mean of 0.66 and a median of 0.72. The percentages of consumers who  
560 scored each product higher than their average scores were also considered. The  
561 correlation between the real percentages and the predicted percentages for all the  
562 products is 0.87.

563

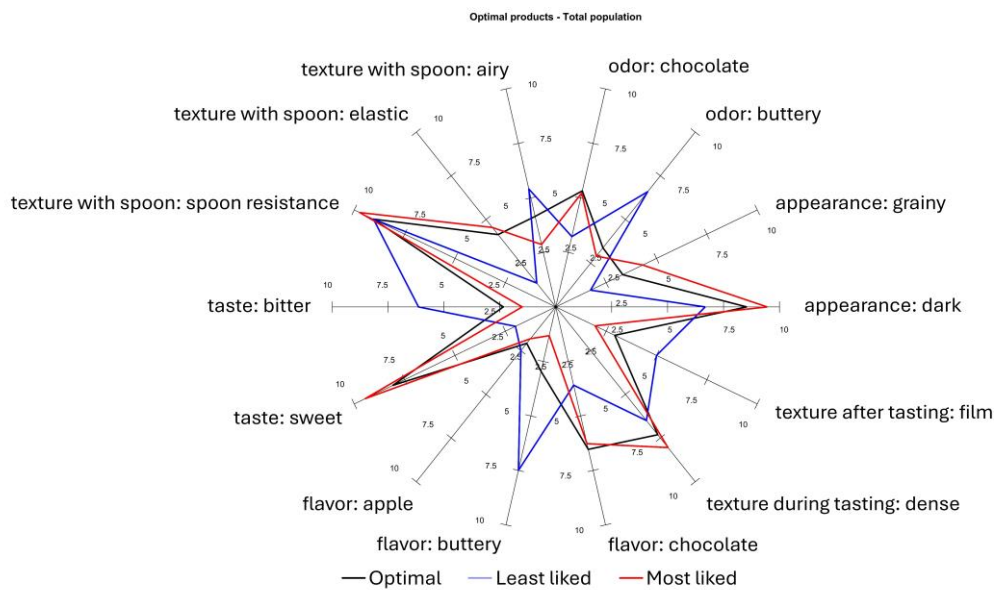
564 The preference map confirmed that consumers liked formulations that balance sweetness  
565 and texture, while minimizing bitterness. The area of high consumer liking was  
566 characterized by formulations that maintained a dense and resistant texture, a  
567 pronounced chocolate flavor, and sweetness. Formulations that felt outside this zone,  
568 particularly those with higher levels of margarine or hazelnut milk, were consistently  
569 rated lower by consumers.

570



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573 **Figure 7: External Preference Mapping with quadratic model showing the highest satisfaction area for the consumers.**

574 The sensory scores of the optimal products obtained with the barycenter method  
575 confirmed these qualitative findings : high values for dark appearance, spoon resistance,  
576 sweet taste, and dense texture during tasting; low values for grainy appearance, buttery  
577 odor, bitter taste and apple flavor (Figure 8).



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581 **Figure 8 : Sensory scores of the optimal recipe with the least and most liked recipes showing the differences of scores for each attribute.**

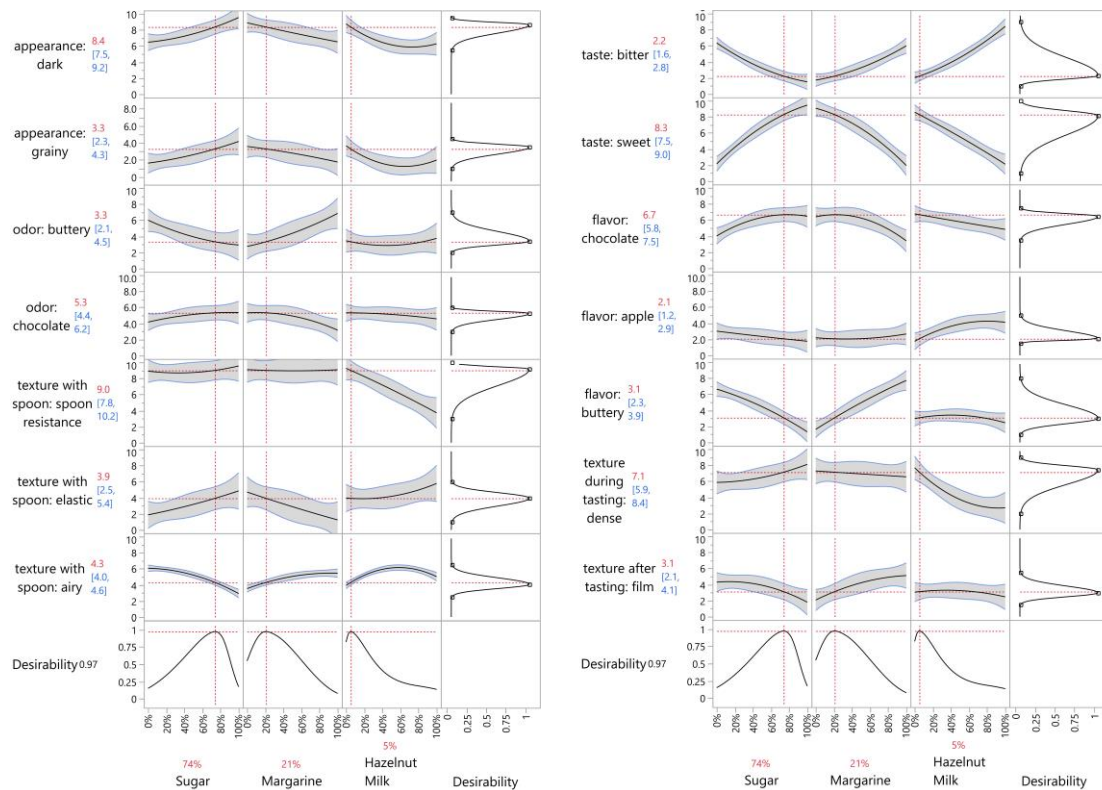
582  
583 **From ideal sensory scores to DoE Factors**

584 In the JMP profiler, each row of plots represented a sensory attribute. For each sensory  
585 attribute, there was a profile trace for each factor. The profile trace was the predicted  
586 response if one factor was changed. The profile trace was surrounded by the confidence  
587 interval of the mean response. Each individual plot contained a horizontal and a vertical  
588 red dotted line. The vertical dotted line for each factor showed its current value. The

589 horizontal dotted line showed the current predicted value of each sensory attribute for  
 590 the current values of the factors. The current predicted value for each sensory attribute  
 591 was shown in red text on the vertical axis with the confidence interval of the mean  
 592 response (Figure 9).

593 At each sensory attribute was attached a desirability function. This desirability plot  
 594 indicated which sensory score was aimed for that attribute. These values were issued  
 595 from the preference mapping: they were the scores of the optimal product (Figure 8).

596



597

598 **Figure 9 : Prediction profiler (Left : from appearance dark to texture with spoon airy; Right : from**  
 599 **taste bitter to texture after tasting : film) showing the desirability functions and the optimal recipe.**

600

601 The maximal reachable value of the global desirability was 0.97 (from “0” being the worst  
 602 to “1” being the best): it corresponded to a mixture of 74% sugar, 21% margarine and 5%  
 603 hazelnut milk. This was the formula for the best product.

## 604 4. Discussion

### 605 4.1 Validity of the Proposed Framework

606 Firstly, the mousse with the optimal formula was produced and evaluated by the panelists  
 607 of stage 3 to compare the sensory scores it should have with the scores it had: the scores  
 608 were very close (Table 4).

609

610

**Table 4 : Comparison of theoretical and actual sensory scores of the optimal mousse**

Attributes	Aimed theoretical values after preference mapping	Actual values after sensory evaluation
appearance: dark	8.6	8.4
appearance: grainy	3.5	3.3
odor: buttery	3.4	3.3
odor: chocolate	5.3	5.3
texture with spoon: airy	4.1	4.3
texture with spoon: elastic	3.9	3.9
texture with spoon: spoon resistance	9.2	9.0
taste: bitter	2.3	2.2
taste: sweet	8.1	8.3
flavor: apple	2.1	2.0
flavor: buttery	3.0	3.1
flavor: chocolate	6.5	6.7
texture during tasting: dense	7.4	7.2
texture after tasting: film	3.0	3.1

611

612 Secondly, to validate the relevance of the methodological framework, a consumer study  
613 was conducted in the fall of 2024, comparing the optimal product with two commercial  
614 products: the leading 'classic' chocolate mousse and the leading 'vegan' chocolate mousse.  
615 A total of 300 participants, specifically recruited outside AgroParisTech (50% females,  
616 and mean age 49.4 years, regular consumers of chocolate mousse) evaluated the products  
617 using a hedonic scale ranging from '0' to '10'. For 133 consumers (44%), the optimal  
618 mousse was preferred to the vegan mousse. This result was encouraging and  
619 demonstrated the potential of the product in the vegan market.

620

621 The sensory reverse engineering framework proved to be an effective tool for optimizing  
622 the formulation of the vegan chocolate mousse to meet consumer preferences. By  
623 integrating sensory data with consumer feedback, the framework allowed a systematic  
624 exploration of ingredient interactions, leading to the identification of an ideal formulation  
625 that balanced sweetness, texture, and flavor.

626

627 This study highlighted the value of integrating traditional sensory analysis techniques  
628 with data-driven methodologies, such as DoE and preference mapping. The use of these  
629 tools provided a more comprehensive understanding of the complex relationships  
630 between ingredients and sensory attributes, ultimately leading to a product that should  
631 be highly favored by consumers.

632

633 Although the proposed method did not significantly reduce time and cost compared to  
634 traditional product development methods (which often rely on expert knowledge and  
635 iterative prototyping), the sensory reverse engineering framework provided a more  
636 structured and efficient approach. By involving consumers early in the design process and  
637 using statistical models to predict sensory outcomes, this framework reduced not only  
638 the number of trials/fails, but also the risk of developing products that fail to meet market  
639 expectations.

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## 640 4.2 Practical Implications

641 The findings of this study had implications for the food industry, particularly in the  
642 development of a plant-based alternative product. Additionally, the use of by-products  
643 like apple pomace aligns with the growing demand for sustainable and environmentally  
644 friendly food products.

645

646 The framework presented in this study can be applied to a wide range of food products,  
647 particularly those that require a careful balance of sensory attributes to meet consumer  
648 expectations. The approach was particularly relevant for developing products for growing  
649 markets, such as vegan or allergen-free products, where the sensory characteristics of  
650 alternative ingredients must be carefully managed to ensure consumer acceptance.

651

652 Moreover, the integration of DoE with sensory description could allow a more precise  
653 understanding of how ingredient interactions influence sensory outcomes.

## 654 4.3 Sustainability and Future Perspectives

655 The inclusion of apple pomace in the vegan chocolate mousse formulation highlighted the  
656 potential of incorporating by-products into food products to promote sustainability.  
657 Apple pomace is a readily available and cost-effective ingredient that, when used  
658 appropriately, can enhance the nutritional value and stability of food products. While its  
659 inherent bitterness can pose a formulation challenge, this sensory attribute may also  
660 appeal to certain consumer segments—such as those who enjoy dark chocolate and bitter  
661 flavors in general. Nevertheless, even among these consumers, the perception of  
662 bitterness remains a matter of dosage, and must be carefully calibrated through  
663 formulation and processing techniques.

664

665 The sensory reverse engineering framework provided a pathway to address these  
666 challenges by enabling the systematic exploration of new ingredient interactions and  
667 their impact on sensory attributes.

668

669 There is a growing need for underutilized raw materials (e.g., sorghum), novel raw  
670 materials (e.g., by-product powders), and innovative processes (e.g., low-water, low-  
671 energy techniques). The principles of sensory reverse engineering are broadly applicable  
672 and could provide valuable insights for developing products that meet evolving consumer  
673 demands.

674 Furthermore, the framework could be extended to include additional dimensions of  
675 product quality, such as nutritional value and environmental impact. For instance,  
676 integrating life cycle assessment data into the optimization process could help ensure that

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677 the final product not only meets consumer’s sensory preferences, but also aligns with  
678 broader sustainability objectives.

## 679 **5. Conclusion**

680 This study introduced and validated a sensory reverse engineering framework for the  
681 development of food products that are optimized based on consumer preferences. The  
682 framework was applied to the development of a vegan chocolate mousse, where  
683 traditional egg-based ingredients were replaced with aquafaba and apple pomace. The  
684 study showed that by methodically incorporating consumer feedback into the  
685 formulation process, products can be developed that meet technical and nutritional  
686 standards while providing the sensory experiences consumers seek.

687

688 The proposed sensory reverse engineering framework successfully identified the ideal  
689 formulation that balanced sweetness, texture, and flavor, resulting in a product that was  
690 highly preferred by consumers. The use of DoE0, preference mapping, and response  
691 surface modeling provided a robust foundation for understanding the complex  
692 relationships between ingredients and sensory attributes, ultimately leading to a  
693 successful product.

694

695 The success of the sensory reverse engineering framework in this study suggests several  
696 avenues for future research, including testing its generalizability across different food  
697 matrices, integrating process-related variables in addition to formulation factors, and  
698 exploring more advanced modeling approaches to enhance robustness and predictive  
699 accuracy.

700

701 Finally, future studies could investigate the potential for scaling up the production of the  
702 optimized formulations identified through the sensory reverse engineering framework.  
703 This could involve investigating the stability and shelf-life of the products, as well as their  
704 performance in different market segments.

705

### 706 **Human ethics statement**

707 *These studies implying humans were carried out in accordance with the international*  
708 *ethical guidelines for research involving humans established in the Declaration of Helsinki,*  
709 *as well as in accordance with a longstanding internal code of conduct for sensory science.*  
710 *Data were collected following the EU General Data Protection Regulation (EU 2016/679).*  
711 *An ethic Committee for research (INRAE, France) approved this study (IRB00013805 /*  
712 *IORG0011649 - [CEPR19](#)).*

713

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716

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