

1 **A FOOD AND BEVERAGE MAP: EXPLORING FOOD-BEVERAGE PAIRING**
2 **THROUGH PROJECTIVE MAPPING**

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31 **1. Introduction**

32 **1.1 Food pairing**

33 Food pairing has been a popular topic amongst scientists, chefs, and researchers who
34 try to find new successful food combinations and identify a pattern in how consumers
35 pair food (Ahn et al., 2011). When studying food pairing, the “food pairing hypothesis”
36 arises, which states that two ingredients that share chemical compounds are more
37 likely to taste (and smell) good together (Simas et al., 2017; Kort et al., 2010; Tallab &
38 Alrazgan, 2016). From a gastronomic approach, flavor pairing could be defined as
39 flavors that, if paired, will produce an experience that is more appreciated than either
40 of the two flavors alone (Møller, 2013). However, not all the flavor combinations are
41 accepted worldwide, as they also heavily rely on culture (Arellano-Covarrubias et al.,
42 2019).

43 Ahnert (2013) and Simas et al. (2017) studied the influence of culture and found that
44 the rules that followed the food pairing are different between cultures. For example,
45 Ahn et al. (2011) found that, in general, both Western and European Cuisine use
46 ingredients that share similar flavor compounds, while East Asian Cuisine does the
47 opposite. Following this last statement, Jain et al. (2015) found that different regional
48 Indian Cuisines followed “negative” food pairing patterns: meaning that the higher the
49 flavor sharing between two ingredients of Indian recipes, the lower the co-occurrence
50 in that cuisine.

51 Besides the influence of culture in food pairing, other authors like Shepherd (2006)
52 stated that the perception of flavor involves many sensory and motor systems. For
53 instance, integral components of our eating experiences arise from all sub modalities
54 of the somatosensory system: fine touch, creaminess, deep pressure (such as
55 crunchiness), temperature, and pain (in the case of the burning sensation of chilis). In
56 other words, an additional layer of olfactive or aromatic coincidence should be added
57 to the act of pairing two or more food products. In this way, Eschevins et al. (2019)
58 reported some pairing principles obtained from French sommeliers and beer experts
59 that could be categorized in “conceptual” (geographical identity and context of
60 consumption), “affective” (consumers’ preferences and emotions), and “perceptual”

61 (aroma, taste, texture); so, when venturing into food pairing research, several aspects
62 should be considered.

63 Traditionally, food pairing research has widely focused on studies with wine and foods,
64 such as cheese (Galmarini, 2020; Harrington & Seo, 2015; King & Cliff, 2005;). Some
65 research studied how certain attributes of wine were affected by different food pairings.
66 To take an example, hollandaise sauce (Nygren et al., 2001) and blue mold cheese
67 (Nygren et al. 2002) were found to affect the perception of wine attributes such as a
68 decrease in sour, bitter and toasted flavors, and an increase in butter flavor, in the case
69 of hollandaise sauce research (Nygren et al., 2001); while buttery and woolly flavors
70 and saltiness and sour taste decreased after tasting dry white wine (Nygren et al.,
71 2002). With similar results, Madrigal-Galan and Heymann (2006) evaluated the effect
72 of cheese before wine consumption and found that some wine attributes such as
73 astringency, bell pepper, and oak flavor significantly decreased when red wine was
74 evaluated after tasting the cheese. Therefore, the consumption of certain foods has
75 been shown to impact the perception of the beverage, and vice versa; consuming a
76 certain beverage is able to modify the perception of certain foods.

77 In a recent study, Kustos et al. (2020) found that appropriate food and wine pairings
78 are positively correlated to liking, sensory complexity, and expected price to pay, and
79 negatively with balance as a slight wine dominance was preferred. Bastian et al. (2010)
80 evaluated wine and cheese matches where consumers rated whether the wine
81 dominated the pair, or the cheese, or if the combination was an “ideal match”. Authors
82 found that wine domination of the cheese does not appear to drive the preference for
83 wine and cheese pairs; it revealed that match perceptions were related to the overall
84 liking for the wine alone. In this line, other studies (Donadini et al., 2012) explored the
85 combination of several beverages with chocolate and found that the liking of a
86 chocolate and beverage pair depended more on the liking for the beverage than for
87 the chocolate or the level of the match of the two.

88 The evaluation of ideal food and beer pairings has also attracted researchers’ attention
89 (Donadini et al. 2013). Donadini et al. (2008) found that the suitability of a food-beer
90 pair was positively correlated to the liking of the beer. In a similar study on craft beer

91 and soup pairings, Paulsen et al. (2015) found that there is a significant effect of the
92 beer type tasted and liking, as well as the dominance of either one of the components
93 can reduce liking and perceived harmony, while the dominance of soup reduced the
94 complexity of the pairing.

95 Regarding the food chemical interactions, some research has focused on different food
96 pairings such as banana with basmati rice, bacon, and extra virgin olive oil (Traynor et
97 al., 2013). The authors suggested that synergistic and/or antagonistic interactions
98 between the volatile compounds in the evaluated foods influenced the ratings of the
99 food pairings. Therefore, the hypothesis of successful food pairings based on the
100 common shared volatiles was not verified. Contrarily King and Cliff (2005), found that,
101 in general, stronger flavorful cheese is more likely to be a good match with a flavorful
102 wine than milder flavorful cheeses. In the same way, Cichelli et al. (2020) studied the
103 aromatic similarity as a congruency of the same flavor. The authors suggested a flavor
104 congruency to enhance the oil-pairing harmony between olive oil with Italian
105 vegetables, where harmony was maximized for olive oil with green and bitter flavor
106 paired with very bitter or pungent vegetables. These last statements followed, to some
107 degree, the food pairing hypothesis: “The more aromatic compounds two foods have
108 in common, the better they taste together,” which according to Klepper (2011), is
109 particularly strong when two foods share aromas that make up their characteristic
110 flavor.

111 However, restricting the food pairing to only the chemical similarity hypothesis would
112 not necessarily lead to a successful food pairing, since all food combinations could
113 have cultural, traditional, and physiological factors (Madrigal-Galan & Heymann, 2006),
114 which makes the pairing more complicated than simply pairing foods that share
115 common key compounds (Traynor et al., 2013). In addition, some of the reported
116 findings are mainly based on professionals’ perspectives and may not reflect how
117 consumers feel (Madrigal-Galan & Heymann, 2006).

118 Some limitations of the study of “ideal pairings” in rather analytical studies have been
119 the use of scales to indicate an ideal match where neither the food nor the wine
120 dominates (King & Cliff, 2005; Bastian et al., 2010; Donadini et al., 2008; Donadini et

121 al., 2013). Another limitation is that only a few products have been tested in the food
122 pairing research and in western countries. A whole set of products and different
123 cultures need to be explored to increase our understanding of ideal food-beverage
124 pairings. In general, food pairing research opens a window of opportunity to apply
125 different methodologies and approaches in the sensory and consumer research field
126 due to the need to study the whole experience of food-beverage and food-food
127 combinations (Galmarini, 2020).

128

129 **1.2 Evaluation of food pairing**

130 Since the study of food pairing became popular in consumer research, different
131 methodologies have been applied to find successful food and beverage pairings as
132 well as to understand the dynamics that explain why consumers pair certain foods with
133 others. Regarding the hedonic side of food pairing, Donadini et al. (2013) explored the
134 consumers' hedonic responses to cheese and beer pairings by using a natural
135 environment of consumption. Consumers evaluate each cheese-beer pairing using a
136 9-point hedonic scale; additionally, a Just About Right scale was used to evaluate each
137 pair for which flavor lingered the most (cheese or beer flavor). Likewise, Bastian et al.
138 (2010) evaluated pairings of wine and cheese in a consumer test in a sensory lab. A
139 Just About Right scale was used to test the "ideal match" of wine and cheese, and the
140 liking of the pairing was rated on a 15 cm hedonic line scale. Harrington and Seo (2015)
141 utilized a Likert-type 9-point scale to evaluate hedonic consumer' responses perceived
142 from wine, food (dark chocolate and goat's cheese), and wine and food pairings.

143 A purely computational approach was taken by Ahn et al. (2011), who explored the
144 impact of flavor compounds on combinations of ingredients by introducing a network-
145 based approach. A bipartite network was built, which consists of two different types of
146 nodes: ingredients used in recipes throughout the world and the flavor compounds that
147 contribute to the flavor of each ingredient, where the natural occurrence of a compound
148 in an ingredient was represented by a link (Ahnert, 2013). The bipartite network
149 projection into the ingredients space represented the flavor network in which two nodes
150 (ingredients) are connected if they share at least one flavor compound. In their study,

151 Ahn et al. (2011) found that North American and Western European Cuisines exhibit a
152 tendency towards recipes whose ingredients share flavor compounds, so in general,
153 these cuisines confirmed the food pairing hypothesis in contrast to East Asian and
154 Southern European cuisines.

155 Eschevins et al. (2018) tested the effect of the aromatic similarity on liking, harmony,
156 homogeneity, complexity, and balance of food-beverage combinations by pairing a
157 lemon soft drink with four dairy products prepared from "Fromage Blanc" (a kind of
158 unsalted cottage cheese), aromatized with lemon, citrus + lemon, vanilla, and
159 strawberry + lemon. In a second experiment, two beers were flavored with lemon and
160 smoky aroma, and savory verrines were aromatized with the same aromas as those
161 used for the beers. For each experiment, consumers tested the pairings using rating
162 scales to evaluate liking, harmony, homogeneity, complexity, balance, and familiarity
163 of pairings. In general, they found that pairings high in aromatic similarity showed
164 increased ratings of harmony and homogeneity, and decreased complexity.
165 Additionally, according to the food pairing hypothesis, the product pair with high
166 aromatic similarity was preferred significantly over the pair the pair with low aromatic
167 similarity.

168 With a different approach, Galmarini et al. (2017) evaluated the impact of wine on the
169 perception of cheese, where the cheeses were dynamically characterized (with and
170 without wine consumption) by using temporal dominance of sensations (TDS) coupled
171 with a hedonic rating on a continuous scale. The researchers concluded that the wine
172 had no impact on the liking for cheese, while the liking of wine was affected by cheese.

173 The reviewed literature only shows a brief compilation of the various methodologies
174 and approaches that have been used in the research of food pairing where, except for
175 the computational methodologies, only a few beverages and food items have been
176 tested at once. The need for a methodology that could be repeated and standardized
177 in the food pairing field (Galmarini, 2020) and the use of more consumer-oriented
178 methods raise the interest in implementing new techniques that could lead to a better
179 understanding of how consumers pair specific types of food and beverages.

180

181 **1.3 Projective mapping**

182 In the present research, projective mapping is presented as a tool for creating maps to
183 better understand preferred food and beverage pairing amongst consumers. Projective
184 mapping is a descriptive method that has been widely used in the sensory field as a
185 method for fast profiling and measurement of consumers' perception (Berget et al.,
186 2019), which provides a map that best reflects the perceived similarity of the evaluated
187 products (Valentin et al., 2016).

188 The primary purpose of projective mapping is to obtain global similarity measurements
189 between products from participants that, in general, are not trained assessors (Valentin
190 et al., 2016). One of the main advantages of this methodology is the avoidance of
191 panelist selection and training, which could impact the cost and time involved in
192 maintaining well-trained panels; likewise, its relative ease of use compared with
193 traditional descriptive models, such as quantitative descriptive analysis (QDA)
194 (Savidan & Morris, 2015), has attracted researchers' attention. Moreover, the
195 undirected nature of projective mapping as a projection technique, and the flexibility of
196 the method, makes it suitable for diverse applications such as preference hedonic
197 frame (Varela et al., 2017; Kim et al., 2019) or to study more complex sensory
198 attributes, for example, the minerality of wines (Heymann et al., 2014).

199 Results from projective mapping can be analyzed with Principal Component Analysis
200 (PCA) or Generalized Procrustes Analysis (GPA) (Gower, 1975; Tomic et al., 2015);
201 additionally, Multiple Factor Analysis (MFA) (Brown et al., 2020) is also suitable
202 because it considers the differences between assessors (Valentin et al., 2016). In the
203 case of analyzing projective mapping with GPA, only two components can be extracted
204 from the data (Tomic et al., 2015), while MFA results could provide more components
205 (Berget et al., 2019).

206 According to Tomic et al. (2015), MFA and GPA typically find quite similar structures.
207 Nestrud and Lawless (2008) previously reported that results from GPA and MFA were
208 also very similar when the methods were applied to data from a single experiment of
209 13 citrus juices evaluated by experienced chefs and untrained consumers. In addition,
210 GPA reduces individual differences between consumers' data by the processes of

211 translation, rotation, reflection, and scaling of the configurations, and consequently, it
212 preserves relative distances between the products in each configuration (Tomic et al.,
213 2015). In this research, the distance and the variability of the consumers' food pairing
214 data is essentially different; thus, adjusting and preserving the space are needed to
215 find a consensus across all individuals. Therefore, in the case of food and beverage
216 pairing, GPA seems to be statistically more suitable for analyzing consumers'
217 information from projective mapping.

218 Traditionally, for projective mapping, the participants are asked to position products on
219 a sheet of paper in such a way that the positions of the products reflect the products'
220 similarity structure (Valentin, 2016). In this research, projective mapping was adapted,
221 to where the positions of the products reflect food and beverage pairings according to
222 consumer preferences: the shortest distance between two products represents a
223 suitable food and beverage pairing. In contrast, the largest distance between two
224 products represents a non-suitable food and beverage pairing.

225 In general, projective mapping has been used for assessing several food products.
226 However, as Galmarini (2020) stated, food products are not usually consumed in an
227 isolated manner; additionally, the author reported that the ingredient and food-
228 beverage interactions are more complex than the study of shared volatiles alone, as
229 food pairing theory states. These statements make it necessary to explore not only the
230 aromatic compounds of food pairing but also the perception and preferences of food-
231 food and food-beverage pairings. On these bases, the present research aims to
232 explore young Mexican consumers' food and beverage pairing by using projective
233 mapping as a consumer-oriented method to create maps that represent successful
234 pairings.

235 **2. Materials & methods**

236 **2.1 Food and beverages selection**

237 According to a previous study (Arellano et al., 2019), beer was the most commonly
238 explored alcoholic beverage due to it being the most consumed alcoholic beverage by
239 Mexicans (Euromonitor International, 2014). However, since other beverages, such as
240 wine and tequila, are also frequently consumed according to the above referenced

241 sources, it was decided to explore not only beer but the most frequently consumed
242 beverages among young Mexican consumers and their respective pairings from a set
243 of frequently consumed food products.

244 The foods and beverages were selected from the information published in Arellano et
245 al. (2019): several phrases, tweets, Instagram and Facebook posts and publications
246 of consumers, related to both beer and food, were extracted from social media and
247 mainstream (Corporate channels or Internet sites. e.g., general news, magazines,
248 newspapers) data, for a one-year period, regardless of the time of day or the place the
249 posts were published. Due to the nature of the extraction process and the privacy
250 policies of some social media platforms, the gender and age of the users could not be
251 registered exactly. From this study, sixty-four foods with a high frequency of being
252 paired with beer were extracted. Analogously, from the information from Instagram and
253 Twitter, thirty-six foods that were popular among young Mexican users were also
254 extracted. From the information, the most frequently paired foods in social media data
255 were selected (Supplementary material 1).

256 A final list of thirty foods (Table 1) and six beverages were selected: soda, white and
257 red wine, tequila, and blond and dark beer, due to the high popularity observed in the
258 previous research, and growing (wine) or high (soda) consumption by Mexican
259 consumers.

260 Table 1

261 30 foods used in the projective mapping task that were extracted from social media data (Adapted
262 from Arellano et al., 2019)

Avocado	Shrimp	Spices	Butter	Bread	Pineapple
Oats	Red meat	Hibiscus	Mango	Potato	Pizza
Salty snacks	Onion	Ginger	Apple	Cucumber	Chicken
Peanuts	Chili	Tomato	Berries	Fish	Cheese
Coffee	Chocolate	Lime	Orange	Pepper	Tortillas

263

264 **2.2 Participant's selection**

265 One hundred Mexican participants were recruited from a Mexican University to perform
266 this exploratory study. The recruitment process was carried out through
267 advertisements, email messages, and personal communication. The inclusion criteria

268 were to be above 18 years of age, and a regular alcoholic beverage consumer (at least
269 once a month); however, consumer habits were not recorded. The gender and age of
270 the participants were registered. Due to the recruitment process, the most expected
271 age segment was 18-25 years old; therefore, the subsequent age categories were
272 defined for intervals of 10 years.

273

274 **2.3 Projective mapping**

275 Several paper cards were designed for each food and beverage (Supplementary
276 material 2) to guarantee that consumers evaluate all food and beverage items in the
277 same way, as if they were testing real products (as usually done in face-to-face
278 research). In addition, the use of images along with the product's name allowed the
279 consumers' perception of the general sensory profile of foods and beverages to be
280 investigated, and not only a specific flavor; furthermore, this approach allowed the test
281 to be applied on different days without having variances in the food and beverages
282 preparation. The use of images for research has been previously used for sorting tests
283 with children (Varela & Salvador, 2014); also, Mielby et al. (2014) compared projective
284 mapping and sorting to a generic descriptive analysis, using visually different pictures
285 of fruit and vegetable mixes. In general, the use of visual stimuli instead of actual food
286 products can minimize the time for sample preparation and the cost of the experiments
287 (Mielby et al., 2014); in addition, in consumer studies, this approach has been
288 increasing in recent years (Kildegaard et al., 2011; Mielby et al., 2012; Arce-Lopera et
289 al., 2015, Varela & Salvador, 2014). In this research, images were used by designing
290 several paper cards (3x4 cm) containing an image of the food/beverage and their
291 respective names (Fig. 1).



292

293

294

Figure 1. Food and beverages paper cards design used in the projective mapping, examples of red wine and berries.

295

296

The projective mapping was performed in a single session. Each participant was asked to first place the beverages on a sheet of paper (60x40cm) (Valentin et al., 2016). The cards' positions reflected similarities or differences between the beverages, so that the closer the beverages were positioned to each other, the greater their similarity. Second, consumers were asked to position each food card on the same sheet of paper so that the cards' positions reflected better combinations between foods and beverages, while the closer a food was to a beverage or another food, the better the food-beverage or food-food pairing, according to their preferences. If some product seemed not to combine well with any food/beverage, the participants were asked to position it further from all the products. Participants could change the positions of the beverage and food cards as often as they needed.

307

To avoid errors in the measurements of the positions of the products on the sheet of paper, the participants were instructed to replicate the food and beverage maps on a computer screen, which was programmed in a similar way, and with similar measurements to those on the sheet of paper, by using the Fizz software® (Mielby et al., 2014). Any further change in the positions of the products on the computer screen was allowed in order to create a map of preferred food and beverage pairings. The

312

313 duration of the task was about ten minutes. Fizz software® (version 2.51 c 02) was
314 used to convert the positions into coordinates, guaranteeing the unit measurements'
315 homogeneity in the dimensions. Finally, the X and Y coordinates of each product for
316 each participant were recorded.

317

318 **2.4 Data analysis**

319 The demographic information of the consumers, such as gender and age, were
320 determined after the recruitment. Regarding the food and beverage pairing information,
321 all food/beverage coordinates for each product and for each consumer were extracted
322 from Fizz® and submitted to Generalized Procrustes Analysis (GPA). A permutation
323 test for GPA (10000 permutations; significance 5%) was performed to test that the
324 consensus map was above chance (Wakeling et al., 1992); and for the consensus
325 coordinates, an Agglomerative Hierarchical Clustering (AHC) was performed
326 (Euclidian distance; Ward's criterion) to find all food items that could be combined with
327 each beverage. The variance within and inter clusters was calculated from 2 to 10
328 clusters to understand the differences across clusters, and better define the final
329 number of clusters. Finally, to test the gender effect, a GPA for each gender was
330 performed and RV coefficient was calculated between female and male GPA'
331 coordinates, as has been previously done for projective mapping data (Tomic et al.,
332 2015; Orden et al., 2021; Vidal et al., 2014b). All statistical analyses were performed
333 using XLSTAT software version 2012.5.02 (Addinsoft, 2019).

334

335 **3. Results**

336 Results from the participants' characteristics are shown in Table 2, the percentage of
337 gender and age was calculated with the total sample of 100 participants. The study's
338 goal was to achieve approximate balance in gender, resulting in 58% of women and
339 42% men. Regarding the participants' age, more participants from 18 to 25 years old
340 responded to the test. Because individual differences were beyond the scope of this

341 study and due to the unbalanced age segments of consumers, no further analysis was
 342 performed on the age segments.

343 Table 2

344 Participant's demographic characteristics (N 100).

	Gender	Age				
	(Biological sex)	(years)				
	Percentage (%)	18-25	26-35	36-45	46-55	Unknown
Women	58	42	13	0	0	3
Men	42	30	7	3	1	1
Total	100	72	20	3	1	4

345

346 3.1 Food-beverage pairing from projective mapping

347 Figure 2 shows a product map from one consumer, where the proximity between
 348 beverages and foods represents the food and beverage pairings.

349



350

351 Figure 2. Food and beverage map from projective mapping with images. Names of the
 352 products are shown in the original language (Spanish) of the test.

353

354 The food and beverage pairing data from projective mapping were analyzed with
355 Generalized Procrustes Analysis (GPA). To explore the effect of gender, a GPA for
356 each gender was performed and RV coefficient between female and male coordinates
357 was calculated. The RV coefficient in the area of projective mapping has been the
358 standard method when comparing matrices (Robert & Escoufier, 1976), and it has
359 been used frequently for comparing data sets and consensus solutions (Tomic et al.,
360 2015). The results of RV coefficients range from 0 to 1, with values closer to 1 indicating
361 a greater degree of similarity between two configurations. Results of RV coefficient
362 between women and men (0.694; p -value<0.001) was relatively high, showing that
363 both women's and men's coordinates were similar, and consequently, that their
364 representation of the food and beverage pairings were comparable. Therefore, the
365 interpretation will be focused only on the overall consensus GPA solution.

366 A PANOVA table (Supplementary material 3) was computed to evaluate the
367 contribution of each Procrustes transformation to the reduction of the total variance in
368 the GPA consensus. Results showed that a reduction of the variance was obtained
369 from the three transformations, so in general, the individual differences between
370 consumers were successfully reduced. Rotation (10.9, p -value<0.0001) followed by
371 translation (8.9, p -value<0.0001) had the greatest effect on reducing variance, while
372 scaling (1.8, p -value<0.0001) had the lowest effect. According to Tomic et al. (2015),
373 the differences in how consumers place the products could be due to two aspects. The
374 first one depends on the differences in the perception of the products, while the second
375 relies on the different ways of using the directions of the mapping sheet and is not
376 related to the differences between products. In this sense, results of PANOVA showed
377 that a large variance reduction of the non-sensory related individual differences was
378 obtained through the Procrustes transformation.

379 A permutation test for GPA was performed to test whether the consensus map was
380 real or a product of chance. The R_c statistic obtained from the permutation test
381 represented the total variance explained by the consensus after the Procrustes
382 transformations, with high R_c values indicating true consensus across individuals. The
383 results showed an R_c statistic (0.153) greater than any of the R_c values from the 10

384 000 permutations (Mean Rc value: 0.065; Maximum Rc value: 0.07) and therefore, that
 385 the consensus configuration was not achieved by chance (100% percentile; level of
 386 significance of 5%) and the reduction of variance by Procrustes transformations was
 387 significant.

388 To understand the differences across clusters, the variance within and inter clusters
 389 was calculated from two to ten clusters. The results from the evolution of the clusters
 390 are shown in Table 3, as a function of the variance within-classes and inter-classes.
 391 As can be seen, from two to four clusters the decrease of the within variance is greater
 392 than those found from five to ten clusters, analogously, the inter-class variance
 393 increased more from two to four clusters than from five to ten clusters. Therefore, both
 394 variances show that 4 clusters are enough to consider as a cutting point in the AHC.

395 Table 3

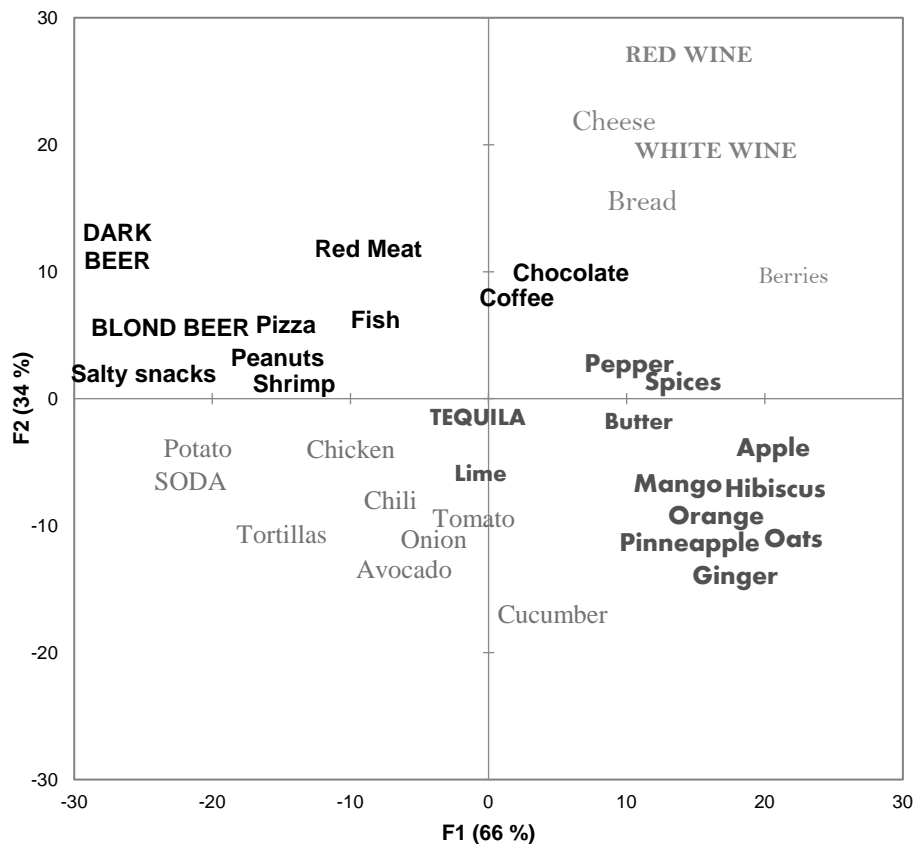
396 Evolution of the within-classes and inter-classes variances. Values shown are percentages.

Number of clusters	2	3	4	5	6	7	8	9	10
Within-class variance	55.5	38.5	27.2	20.1	16.2	12.6	11.5	10.5	9.0
Inter-class variance	44.5	61.5	72.8	79.9	83.8	87.4	88.5	89.5	91.0
Total	100	100	100	100	100	100	100	100	100

397

398 In general, projective mapping analyzed with GPA followed by AHC provided a suitable
 399 and easy interpretation of the food-beverage pairing from Mexican users. According to
 400 the consensus of the participants' preferences (consensus GPA map), the shortest
 401 distance between two products represents a better food and beverage pairing. To
 402 obtain data about which foods pair well with each beverage, an AHC was applied to
 403 the GPA consensus coordinates. The results clustered all food and beverages into four
 404 groups. The main finding is that each beverage could be clustered in an independent
 405 group along with different foods that people combined. The first group clustered both
 406 beers together, the second one grouped both wines, the third cluster contained Tequila
 407 and the last one contained soda. Figure 3 represents the clusters obtained, where each
 408 group included all the foods that paired well with each beverage, according to
 409 consumer preferences.

410



411

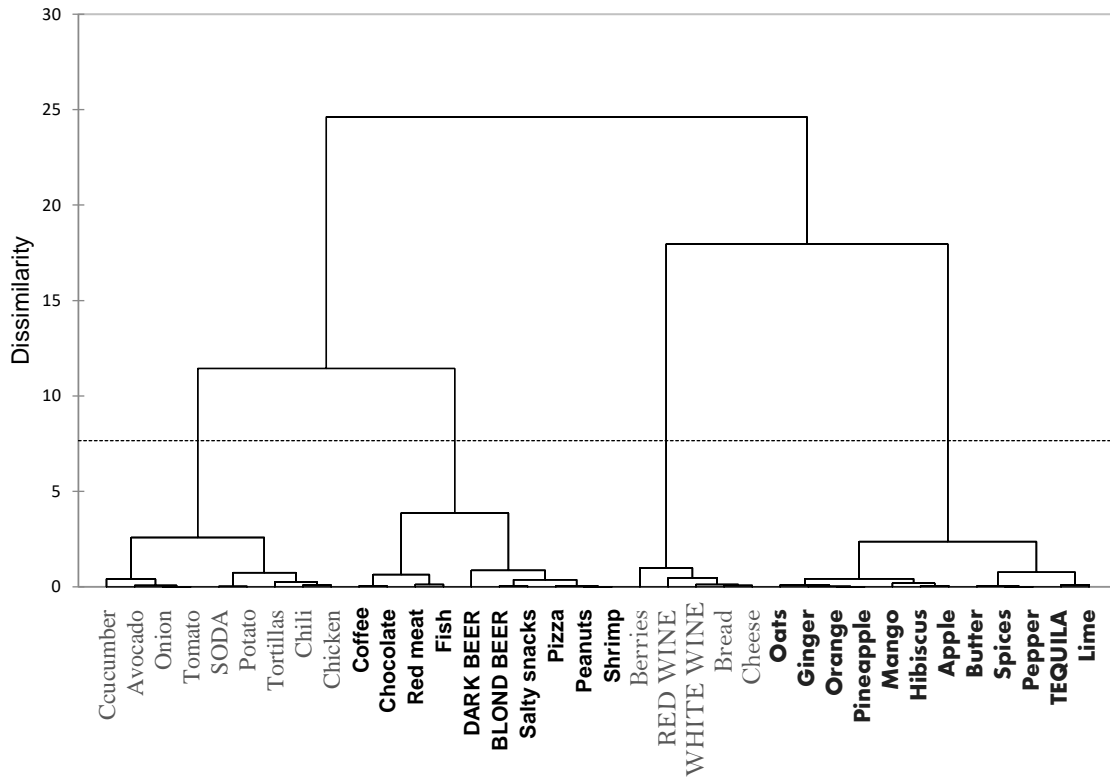
412 Figure 3. Food-beverage pairing map for AHC of GPA. The hierarchical clustering is
413 represented by similar gray color and font. AHC shows that beverages, and their respective
414 food pairings, could be clustered into 4 groups.

415

416 Concerning the beverages, some of the map patterns were that dark and blond beer
417 were clustered in the same group, along with some products such as salty snacks,
418 pizza, peanuts, shrimp, red meat, and fish. In the case of wine, both red and white
419 were clustered only along with cheese, bread, and berries; regarding Tequila, it was
420 clustered with lime, which Mexican people usually combine with this beverage, also,
421 butter, spices, pepper, and several fruits were grouped together. Soda was grouped
422 with chicken, chili, potato, some vegetables, and tortillas, a popular product that
423 Mexican people combine with their regular meals.

424 From the dendrogram obtained from AHC, additional information could be extracted.
 425 For instance, for each cluster, the food items closer to the beverages represented a
 426 better pairing than the food items further from the beverages. Figure 4 shows the
 427 dendrogram obtained from the AHC.

428



429

430 Figure 4. Dendrogram from AHC of the GPA. The hierarchical clustering is represented by
 431 similar gray color and font.

432

433 Some of the most consensual pairings could be identified from Figure 4. Potato,
 434 tortillas, chili, and chicken were closer to soda than cucumber, avocado or onion,
 435 representing a better food and beverage pairing in the cluster. In the case of beers,
 436 both dark and blond were closer to salty snacks, pizza, peanuts, and shrimp than fish
 437 and red meat. Regarding wine, both red and white were close to bread and cheese.
 438 Finally, Tequila was close to lime, and further from pepper and spices, which

439 represented a better food and beverage pairing according to the consensus of
440 consumer preferences.

441

442 **4. Discussion**

443 The present study aimed to explore Mexican consumers' food and beverage pairing
444 using projective mapping as an innovative technique, analyzed by Generalized
445 Procrustes Analysis (GPA). The analysis of projective mapping provided maps in which
446 the proximity between products represents suitable food and beverage pairing
447 according to the consumers' preferences.

448 The results from the PANOVA of the GPA showed that, in general, the individual
449 differences between consumers were successfully reduced, and therefore, only the
450 perception of the food and beverage products was assessed and not the individual
451 differences across configurations. In other words, the reduction of the variance was
452 lower when shrinking or stretching the individual map configurations until they were as
453 similar as possible (scaling) to each other. On the other hand, when the configurations
454 were rotated/reflected to agree with another map (rotation) or were moved to the
455 middle of the mapping sheet (translation) (Tomic, et al., 2015), a higher reduction of
456 the variance was obtained. These results suggest that consumers used different ways
457 to position the products in terms of distances to represent the similarities and
458 dissimilarities across the products and their pairings. This difference on the use of the
459 distances across participants is better analyzed with the GPA, compared to other
460 methods such as MFA (Berget et al., 2019).

461 The result of the R_c statistic from the permutation test was 0.153, showing that the
462 consensus was highly significant at 5% level. Tomic et al. (2015), in their research
463 comparing simulated and real data sets from mapping experiments, reported that
464 relatively high values (of 0.5 and 0.7) of R_c are obtained when the assessed products
465 are "simpler," such as apple juices, while low values are reported for more complex
466 products, such as coffee or wine. In the research published by Tomic et al. (2015), only
467 one type of product was evaluated in each study, in contrast with this research, in

468 which several complex products (wine, coffee, beer, and food items) were tested at
469 once, which could have impacted the results of the R_c value.

470 In order to find which foods paired well with each beverage, an AHC was performed to
471 the GPA consensus coordinates. As shown in Table 3, the inter-class variance had a
472 higher increase until 4-5 clusters, while the within-class variance decreased by the
473 same number of clusters and, therefore, provided enough evidence of differences
474 between clusters, and similarities between the products in each cluster. As one of our
475 objectives was to pair all foods with each beverage, 4 clusters were selected;
476 otherwise, with 5 clusters, a set of food products would remain with no beverage to be
477 paired with. The results split up all beverages into different clusters, reflecting that
478 consumers generally considered the beverages as different.

479 Regarding the food pairings, several food items were clustered along with the
480 beverages; for example, both beers (dark and blond) were clustered with salty snacks.
481 In this sense, previous research has also reported that beer is regularly consumed with
482 snack foods in Western Cultures (Pettigrew & Charters, 2006) and associated with
483 purchasing fattier food items (Johansen et al., 2006). With similar findings, Donadini et
484 al. (2008) found that pizza is a good pairing consumed with this beverage, which
485 agrees with the AHC of the GPA, where pizza, shrimp, and peanuts, were also
486 clustered along with beer in our study. In the case of wine, both red and white wines
487 were clustered along with cheese and bread, which are widely reported as good
488 combinations (King & Cliff, 2005; Bastian, 2010; Harrington, 2015).

489 The food and beverage pairings found in this research were not based on a flavor
490 similarity approach but on consumer acceptance and perception which could generally
491 rely on consumption habits in Mexico. For example, lime was clustered with Tequila,
492 which is a highly accepted combination for younger Mexican consumers. Chili was
493 clustered along with soda and several foods such as tortilla, chicken, tomato, and
494 onion, which could reflect the Mexican behavior of adding chili to almost all food
495 products in regular meals; as Rozin and Schiller (1980) stated since 1980, chili is a
496 ubiquitous feature in the Mexican gastronomy, in other words, the chili pairing in
497 Mexican consumers is more a matter of culture than flavor similarity.

498 In this study, popular foods and beverages among young Mexican consumers were
499 tested; however, it is widely reported that cultural context influences consumer
500 preferences and that beverage consumption with specific foods is a significant factor
501 in distinguishing cuisines (Harrington et al., 2008). Therefore, since consumer culture
502 is also a key component in food pairing and that little cross-cultural research can be
503 found regarding food and flavor pairing (Galmarini, 2020), it could be interesting to
504 assess the same set of products, as well as different popular foods, in other cultures,
505 to evaluate the differences/similarities of acceptable pairings between consumer
506 preferences. For example, with French consumers, who are known to have an
507 extensive wine culture, the food and beverage pairings could have been different from
508 those found in this research; analogously, the inclusion of other traditional beverages
509 for Mexican consumers, such as Mezcal or Pulque, could have also yielded different
510 results.

511 Regarding the data analysis, the RV coefficient was used to test the similarities
512 between women's and men's GPA coordinates. Vidal et al. (2014a) reported that this
513 analysis is a good predictor of similarity. Results of RV coefficient between women and
514 men was high, representing similar configurations, and therefore, the perception of
515 suitable food and beverage pairings was also similar between male and female
516 consumers.

517 Previous research has reported that gender influences the habits and preferences of
518 alcoholic consumption, e.g., Jimborean et al. (2021) found that Romanian male
519 students drink alcoholic beverages to relax or socialize and, in general, preferred beer,
520 while females consume alcohol for the beverage's taste or flavor and their favorite
521 beverage was wine. In this sense, gender differences between young adults could play
522 a role in the preferred alcoholic beverages (Martínez et al. 2017) and could impact the
523 food and beverage pairing preferences of consumers. In an article on stereotypes and
524 alcohol consumption, Rodrigues et al. (2020) talk about the gender differences across
525 Mexican consumers, in terms of biological (sex) differences, and cultural gender
526 differences. However, in this study, and as both beer and wine were tested, gender
527 had no effect on food pairing.

528 This research showed the use of projective mapping for exploring food and beverage
529 pairings, which produces maps that visually represent the consumers' preferences for
530 pairing specific food products. With the aim of exploring food-pairing preferences of
531 younger Mexican consumers, neither the share volatile compounds, from food-pairing
532 theory, nor the concentration or detection threshold of the products were considered,
533 only the consumer's perceptions of food and beverage combinations.

534 Some advantages can be highlighted in projective mapping as a methodological
535 approach. In this research, no hedonic or rating scales were applied to evaluate
536 consumer acceptance; the distance between food-food and food-beverages was used
537 as a unit measurement for preferred food-pairing instead. Although the distance and
538 the variability of the consumers' food and beverage pairing data could be essentially
539 different, the adjustment and preservation of the space to find a consensus across all
540 individuals was reached using GPA. The projective mapping approach allowed the
541 evaluation and visualization of consumer preferences for a whole set of products
542 simultaneously, in which a closer position between foods and beverages reflected a
543 better combination of the items.

544 With the purpose of exploring consumers' preferences according to food consumption
545 habits or traditional manner of consumption, the paper cards were designed only as a
546 guide of isolated products. However, consumers were free to create a whole map of
547 how they usually combined their foods and not how a product should be served. Also,
548 consumers did not receive a description of what a "good combination" is, no definitions
549 of an ideal match, balance, or harmony; nor were complementary or similarity matching
550 in the products defined, which helped avoid biasing consumer perception of certain
551 combinations. Additionally, by allowing consumers to position a "non-combinable" item
552 further from all products, the methodology could explore if some food items were not
553 suitable to be combined; however, this tendency was not observed in the maps
554 obtained.

555 Although projective mapping was an effective and practical approach for exploring
556 food-food and food-beverage pairings, the study had some limitations. Traditionally, a
557 pairing usually starts with the food, and it is the beverage which accompanies the food.

558 Here, however, we inverted the task as our research interest was exploring which foods
559 would pair well with specific beverages. Additionally, in the projective mapping task, it
560 was more manageable for consumers to start with visualizing the six beverages instead
561 of the thirty food items. In further analysis, this aspect should be considered; however,
562 it will depend on the study's objectives.

563 Some other factors, such as age, gender, and other demographic variables, should be
564 considered in food pairing evaluation (Galmarini, 2020); however, in this research, no
565 differences in food and beverage pairing could be found between female and male
566 consumers. However, it could be a matter of the relatively low sample size, or that the
567 stimuli used were too similar for the consumers, and therefore culture has a bigger
568 effect than gender. In the case of the age of participants, it has been reported that it
569 could impact consumers' habits and preferences, e.g., Garcia et al. (2013) reported
570 that wine is the most frequently consumed drink among Spanish people over the age
571 of 35, while consumers under 35 frequently consumed other drinks, such as beer. In
572 this study, consumers were recruited only from a university in Mexico City from a
573 narrow age range (18 to 25 years). Further research should include older consumers
574 over 25 years old to test a potential age effect.

575 Another limitation to consider is the use of images instead of real food products. While
576 several studies have used real food products to test food pairing, in this study, due to
577 the high number of food and beverages tested, images were used only as a guide for
578 consumers' perception homogeneity. So, this research provides an overview of what
579 consumers perceived to be a suitable food and beverage pairing, based on their
580 previous experiences. Further research must explore if the found pairings with images
581 agree with real food products. In general, several aspects should be considered to
582 follow this food pairing approach. Demographic variables, the use of real food instead
583 of images, the evaluation of different food products, and the comparison of different
584 cultures, could greatly interest the food pairing field.

585 In general, it was possible to relate a whole set of food items to a specific beverage or
586 group of beverages. In some cases, such as wine, the pairings were previously
587 reported for other cultures, while other pairings were specific to Mexican culture.

588 Additionally, some food items were found to pair better than others. Overall, and
589 according to the results, the exploration of food and beverage pairing through
590 projective mapping, and analyzed through GPA, seems to be a suitable tool for
591 exploring food and beverage pairing, and from which it was possible to obtain a
592 complete food and beverage map that represented the better food combinations for
593 consumers. However, the various aspects discussed above should be considered for
594 further research exploring the proposed methodological approach.

595

596 **Conclusions**

597 This research showed that projective mapping was an effective technique to explore
598 food-beverage pairings by producing maps representing how consumers combine
599 specific foods and beverages. From these maps, it was possible to identify some
600 patterns according to consumers' preferences, in which gender had no effect, meaning
601 that consumers' culture was more important than gender. In general, GPA was a
602 valuable tool to analyze and visualize consumers' food and beverage pairing data.

603 Some of the limitations that arise when analyzing the results are the relatively small
604 sample size, the fact that all participants were young Mexican consumers, and that
605 they come from a specific region in the center of Mexico. As previously suggested,
606 culture could have a bigger impact than gender; the fact that consumers come from
607 different cultures or from different age groups, can bring changes to flavor pairing, and
608 has yet to be explored.

609

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618 **Paula Varela:** Conceptualization, Supervision, and Writing-Reviewing and Editing.

619 **Carlos Gómez-Corona:** Conceptualization, Supervision, and Writing-Reviewing and
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621 **Héctor B. Escalona-Buendía:** Conceptualization, Supervision, and Writing-
622 Reviewing and Editing.

623 **Araceli Arellano-Covarrubias:** Methodology, Formal Analysis, Investigation, and
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625

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