International Journal of Gastronomy and Food Science 33 (2023) 100795

Contents lists available at ScienceDirect

International Journal of Gastronomy and Food Science

journal homepage: www.elsevier.com/locate/ijgfs

Computational gastronomy: A study to test the food pairing hypothesis in Turkish cuisine

Murat Doğan [a,*], Ahmet Hakan Değerli [b]

[a] Istanbul Gelişim University, Faculty of Fine Arts, Department of Gastronomy and Culinary Arts, TR, 34310, Istanbul, Turkey
[b] Istanbul Bilgi University, Faculty of Applied Sciences, Department of Gastronomy and Culinary Arts, TR, 34060, Istanbul, Turkey

ARTICLE INFO

Keywords:
Computational gastronomy
Food pairing
Gastronomy
Turkish cuisine
Turkish regional cuisines

ABSTRACT

This study adopts computational gastronomy methods to test the food pairing hypothesis. For this purpose, Food Pairing Index values (the average number of shared flavor molecules between ingredient pairs) were calculated for recipes from seven local cuisines in Turkey. These values were examined for correlation with user ratings of recipes, and compared with the FPI values of randomly generated recipes. Additionally, the contribution of individual ingredients to the FPI values and the frequently used ingredients in the cuisines were analyzed. The results revealed that FPI values were not significantly positively correlated with user ratings, suggesting that the food pairing hypothesis cannot be fully supported. Also, comparisons with randomly generated recipes show that FPI values are heavily influenced by the frequency of ingredient usage in kitchens. In particular, positive food pairing behavior was observed in some regional cuisines, while negative food pairing behavior was found in others. However, these patterns were consistent with the similarities observed in other kitchens. Overall, the findings, when evaluated together with previous findings and criticisms, show that the food pairing hypothesis and the current computational gastronomy approach to it are partially successful in food pairing.

1. Introduction

Combining and pairing food ingredients are important skills for chefs, but a complete lack of understanding of flavor and aromatic components creates challenges for them. New knowledge about food enables the creation and development of new tastes (Cheng et al., 2011). Although significant progress has been made in the field of food science, our understanding of the intricate nature of food remains quite limited. However, the *"food pairing hypothesis"* (Varshney et al., 2013; This, 2014; Goel and Bagler 2022) suggests that flavor compounds are more likely to complement each other in recipes. In addition, the hypothesis suggests that *"foods with many shared taste molecules will exhibit better compatibility."* Both culinary professionals (Blumenthal, 2008) and scientific researchers (Kort et al., 2010; Ahn et al., 2011) have taken an interest in this hypothesis. Also, the book *"The Art and Science of Food Pairing,"* published by Coucquyt et al. (2020) et al., has given a thousand food pairings, claiming that it will change the way humanity eats. Although the flavor components of foods are still not fully explored, there is increasing interest in food pairings among chefs (Spence and Youssef, 2018; Spence et al., 2017; Vandevelde, 2023). In this context, different studies have been carried out considering the compatibility of food components (Caporaso and Formisano, 2016).

When examining the history of gastronomy, it can be argued that the origins of food pairing can be traced back to the ancient Greeks and Romans. They paired foods in their sophisticated kitchens based on taste, flavor, and texture. In these cuisines, salty foods were paired with bitter ones, while sweet foods were paired with sour ones (Harrington, 2007; Montanari, 2006). During the Middle Ages, as in all world cuisines, spices were widely used in European culinary practices to impart complex flavors to dishes, often being combined with other flavors to create sophisticated meals (Freedman, 2020). However, from ancient times until the 19th century, food pairing studies were solely based on chefs' experiences and trial-and-error methods (Vargas-Sánchez and López-Guzmán, 2018). With the advancements of modern science, scientists have started studying how they influence the chemical composition and flavor of foods. These studies have paved the way for the development of a set of principles for the trending hypothesis of food pairing today (Tallab and Alrazgan, 2016; Varshney et al., 2013; De Klepper, 2011; Ahn et al., 2011).

The compatibility of organic compounds in food and beverages was first suggested in 1994 (Kurti and This-Benckhard, 1994a, 1994b). Kinouchi et al. (2008) statistically examined 3000 recipe components

* Corresponding author.
E-mail addresses: mdogan@gelisim.edu.tr (M. Doğan), ahmet.degerli@bilgi.edu.tr (A.H. Değerli).

https://doi.org/10.1016/j.ijgfs.2023.100795
Received 24 February 2023; Received in revised form 3 August 2023; Accepted 11 August 2023
Available online 13 August 2023
1878-450X/

from English and French cookbooks and showed that recipes are a valid tool in determining cooking preferences, while the presence of ingredients and recipes that match existing ingredients are more socially preferred.

Blumenthal (2002) was one of the first to suggest this hypothesis in his article in The Guardian, and it wasn't until François Benzi mentioned that hypothesis to him in a scientific workshop (De Klepper, 2011). However, it remains unclear whether Benzi put forward this hypothesis or whether he also heard it from someone else. However, we can state that these claims or applications wouldn't be possible without a database regarding flavor compounds in food, which seems to have been first established by the book *"Volatile Compounds in Food"* in 1963 (Nursten, 1986). This book then had six more volumes until 1996, extending the data gradually (Nijssen, 1996; Reineccius, 1991), and was also the database used by Blumenthal and François Benzi (De Klepper, 2011). Also, bioengineer Bernard Lahousse, who is the founder of the company *"Foodpairing"*, and chemist Martin Lersch, who tested and explored the hypothesis on his blog *"Khymos"* with his readers, had a significant contribution to the progression and recognition of the hypothesis (De Klepper, 2011).

The food pairing approach continues to guide chefs in designing versatile and creative dishes by systematically identifying the elements that chemically reveal flavor. Its main purpose is to enable new menu designs, to discover the best possible paired food and beverage combinations while making these designs, and to explain if there are chemical contrasts between pairing foods. Thanks to food pairing, a more creative, innovative, and flexible kitchen can be created. Authentic recipes that can be created with a modern touch, innovative flavors that appeal to different palates, and delicious combinations that bring local and international cuisines together are possible with food pairing (Spence, 2022; Nyati et al., 2021).

In addition to the use of the food pairing hypothesis in the industry and testing it in experimental studies, *"computational gastronomy,"* Ahnert (2013); Goel and Bagler (2022), which is a relatively new discipline and defined as *"the approach based on the use of data science and computer technologies in the understanding and development of food,"* is one of the areas of interest in this hypothesis. Computational gastronomy emerged from the exploration of traditional recipes employed in kitchens, as well as the molecular and flavor components of food (Goel and Bagler, 2022). Asking emerging interdisciplinary culinary questions, this discipline seeks answers using culinary data collection and statistics, machine learning, natural language processing, pattern mining, and chemo-informatics methods (Ahnert, 2013). In addition, the field of computational gastronomy includes food pairing, the molecular basis of taste, the health effects of food, new recipe creation algorithms, and models of culinary evolution (Shukla and Ailawadi, 2019).

In this context, in previous studies, the food pairing hypothesis was tested in American, European, and Asian (Ahn et al., 2011), Arabian (Tallab and Alrazgan, 2016; Al-Razgan et al., 2021), and Indian (Jain et al., 2015) cuisines, and it was concluded that some of these cuisines had a positive and some negative food pairing tendency. On the other hand, no such study has been found on Turkish cuisine. Therefore, this study is aimed at testing the hypothesis on a data set consisting of the recipes of the cuisines of the seven geographical regions of Turkey and determining the most frequently used ingredients in the relevant cuisines and the ingredients that contribute most to the (positive or negative) food pairing.

2. Methodology

The aim of the study is to investigate food pairing hypothesis in Turkish cuisine. As this hypothesis basically assert that ingredients with higher amount of common flavor molecules taste better together one can infer that a "good tasting" recipe will have more common molecules among its ingredients comparing with a random or a bad tasting recipe in general. Also in the studies the opposite have shown to be true that in some cuisines recipes tend to have significantly lower FPI than randomized cuisines.

This study uses computational gastronomy in several ways to test the hypothesis in Turkish cuisine using data from a well-known Turkish recipe website. Firstly we hypothesized that recipes ratings and number of users who saved the recipe will correlate with recipes' FPI as they reflect users liking. And secondly as recipes can be seen as composition of ingredients that selected culturally according to liking of individuals, we hypothesized that they will have significantly higher or lower FPIs than random recipes. Also we consider "amount of ingredients in recipes and frequency of ingredient use in Turkish cuisine and regional cuisines" while creating the randomized control cuisines in order to reduce bias. Therefor hypotheses of this study was formed as shown in Table 1.

2.1. Data collection

In the study, two sets of data were used: data on the ingredients that make up the dishes (recipes) and data on the aroma molecules contained in these ingredients. The data on the recipes were obtained from a popular Turkish recipe site (www.nefisyemektarifleri.com), and in order to include only the dishes of Turkish cuisine in the dataset and to be able to categorize them under related regional cuisines, 81 cities of Turkey were scanned, and the recipes containing one of the names of these cities were included in the dataset. Recipes are then categorized according to the regions where the cities are located.

Data on flavor molecules were obtained from the FlavorDB2 database (https://cosylab.iiitd.edu.in/flavordb2/) presented by Grover et al. (2022), and the dataset generated from Burdock's (2004) Fenaroli's Handbook of Flavor Ingredients in the work of Ahn et al. (2011). Also, for ingredients that are often found in recipes but not in the flavor data sets, such as grape leaves, sumac, tail or tallow fat, etc., data from other studies in the literature were used (Bahar and Altug, 2009; Hebash et al., 1991; Nurjuliana et al., 2011).

This study used web data for recipes like many other studies (Ahn et al., 2011; Issa et al., 2018; Jain et al., 2015) because of the ease of obtaining, sorting, and preparing digital data compared to printed alternatives. But as these recipes are shared by users, there are recurring recipes in the dataset, unlike a book. These recurring recipes are kept for the correlation analysis but excluded in the other analyses as popular dishes can otherwise overbalance and bias the data.

Also, as the dataset for flavor molecules doesn't include all the items in recipes, several transformations had to be done on recipes. The processed ingredients and composite ingredients have been replaced by the sub materials from which they are composed. Ingredients that do not contain volatile components and are used to add color or texture to the food (baking soda, baking powder, food coloring, etc.) are excluded from the recipes. And for the ingredients that aren't replaceable and appear at low frequencies, recipes including them are excluded. While

Table 1
Hypotheses about the food pairing index.

Hypothesis	Description
H_1	There is a correlation between the FPI values of the recipes and the user scores.
H_2	There is a correlation between the FPI values of the recipes and the number of savings.
H_3	Ingredient choices in regional cuisine recipes tend to have significantly higher or lower FPI values than a random ingredient choice, regardless of recipe size.
H_4	Ingredient choices in regional cuisine recipes tend to have significantly higher or lower FPI values than a random ingredient choice, regardless of the frequency of ingredients among all regional cuisines and recipe size.
H_5	Ingredient choices in regional cuisine recipes tend to have significantly higher or lower FPI values than a random ingredient choice, regardless of the frequency of ingredients in the regional cuisine and recipe size.

some other studies exclude the ingredients and keep the recipes for unknown flavor profiles (Al-Razgan et al., 2021), this approach isn't adopted in this study as it changes the dishes and potentially the food pairing index. These mentioned transformations aren't made for the qualitative evaluation to keep ingredients in their originally mentioned form, as FPI calculation is not necessary for these analyses. For the reasons listed above, we end up with three datasets at the end of the data organization, as shown in Table 2.

2.2. Limitations of the study

First of all, as this study utilizes recipes from a single website and includes them by the cities mentioned in the titles, it may not be appropriate to generalize the results to Turkish cuisine. Also, as the food pairing approach only considers the flavor data obtained from several databases, it may not successfully reflect the flavor profile of original ingredients in the regions, as they can substantially vary according to species, growing conditions, and terroir. Also, this approach assumes the flavor profile of these ingredients will remain the same after the preparation, which isn't the case considering the chemical reactions and evaporations during the cooking. Ahn et al. (2011) stated that the preparation method is as effective on taste as the ingredients that make up a dish. It is also possible that the aroma molecules in the food change during cooking (Spence et al., 2017). In addition, volatile odor molecules are dispersed in the oral cavity as a result of the disintegration of different food matrices in the mouth and their interaction with saliva during the tasting of food. Thus, volatile molecules that significantly affect the perception of aroma can be released in different ways (Noble, 1996). Finally, along with the fact that it doesn't take several factors into account, such as ingredient amounts, differences due to different species and growing conditions, and changes during cooking, as this calculation is neither based on consumer perceptions nor tries to simulate them, it shouldn't be expected to give a proper reflection of how consumers will perceive these foods in real-life conditions.

2.3. Analysis of data

Several analyses were carried out on the collected data in accordance with the purpose of the study. First of all, FPI was calculated for each recipe using the collected recipe and flavor molecule data. FPI can be calculated by summing the number of flavor molecules shared by each ingredient pair in a recipe and dividing it by the number of ingredient pairs, as expressed by the following formula (Ahn et al., 2011).

$$N_s(R) = \frac{2}{N_R(N_R - 1)} \sum_{i,j \in R, i \neq j} |C_i \cap C_j|$$

Here Ns expresses the mean number of shared compounds in a recipe, which we referred to as the Food Pairing Index (Goel and Bagler 2022), N_R expresses the number of ingredients in a recipe, $2/(N_{R}*(N_{R-1}))$ gives the reciprocal of the number of ingredient pairs in recipe and $Ci \cap Cj$ expresses the amount of common flavor molecules between ingredients i and j. For example, for a recipe with three ingredients, FPI will be (1/3)* $(C_1 \cap C_2)+(C_1 \cap C_3)+(C_2 \cap C_3)$. Even though calculations are made upon ingredients pairs, as FPI was obtained with the average shared molecules of all possible pair combinations, it reflects the overall food pairing of recipes.

Table 2
Datasets used for analyses.

Dataset	Analyses	Data Organization
1	Correlation Analysis for H1 and H2	-Ingredient transformations[a]
2	Qualitative evaluation of ingredient uses (Frequency and UCI)	-Excluding recurring recipes
3	Comparing FPI values with control cuisines (Wilcoxon test) and examining contribution of individual ingredients on FPI	-Ingredient transformations[a] -Excluding recurring recipes

[a] Include removing recipes with unknown flavor profiles.

Then, three control cuisines were created for each regional cuisine to evaluate whether the values obtained were significantly lower or higher than a value that would be expected to occur randomly, and FPI was calculated for each recipe in them. In all three of the control cuisines created, the number of recipes in the actual regional cuisine and the number of ingredients in the recipes were preserved, and ingredients were selected among the ones used in the actual cuisine. In the first control cuisine, the probability of choosing each ingredient was kept equal. In the second control cuisine, ingredients were selected randomly based on their frequency in the total of all seven regions, and in the third control cuisine, based on their frequency in the regional cuisine to be compared. Since the data set is relatively small, the same process was performed ten times for each control cuisine, and the average FPI values of the control cuisines were calculated as mentioned above.

Hypotheses are tested after this calculation. After the Kolmogorov-Smirnov test, it was observed that the data did not follow a normal distribution, and therefore non-parametric tests were used to test the hypotheses. H_1 and H_2 was tested with Spearman's rho correlation test and H_3, H_4 and H_5 was tested with one-sample Wilcoxon signed-rank test.

In addition, the contribution index was calculated for each ingredient to examine the effect of the ingredients on the positive or negative food pairing behavior of the cuisines, as done in many previous studies (Ahn et al., 2011; Issa et al., 2018; Jain et al., 2015; Singh and Bagler, 2018). The rationale for this calculation is Ahn et al. (2011)'s investigation of whether the positive or negative food pairings seen in different cuisines are largely explained by a few ingredients. The contribution index was obtained by subtracting the average FPI of the regional cuisine from the average FPI calculated if the ingredient was removed from all the recipes in the cuisine. For example, if the average FPI value calculated for all the recipes is 100 and the average FPI calculated after removing the tomato from each recipe containing the tomato is 93, then the tomato's contribution index is 100-93 = 7.

For each regional cuisine, frequency (number of recipes containing the ingredient) and percentage (frequency/total number of recipes from the region) were also calculated, and the most commonly used ingredients are reported. Besides this, as the most commonly used ingredients were mostly common across regions, the usage comparison index (UCI) was calculated by dividing the percentage of use of a specific ingredient in the recipes of the regional cuisine by the percentage of use of the same ingredient in all cuisines to determine the characteristic ingredients of the regions.

$$UCI = \frac{\text{The percentage of use of the ingredients in the recipes of the regional cuisine}}{\text{The percentage of use of the ingredients in all cuisines}}$$

3. Results and discussion

As previously mentioned, three datasets to be used in different analyses were obtained after the data organization. The number of recipes and average ingredients for the relevant data sets are given in Table 3.

The Aegean and Marmara regions, respectively, had the lowest number of recipes in the 2nd and 3rd datasets, while similar numbers of recipes were obtained from other regional cuisines. Considering the number of ingredients in the recipes, the lowest number of ingredients per recipe was found in the Black Sea cuisine, and the most in the Mediterranean and Southeastern Anatolian cuisines (Table 3).

Firstly, correlation analysis was performed on dataset 1, correlation coefficients were -0,047 ($p < .001$) for the correlation between FPI and user ratings and -0.015 ($p = 0.112$) for the correlation between FPI and number of saves the H_1 and H_2 hypotheses could not be supported since no significant positive correlation could be found between FPI values

Table 3
Recipe and ingredient numbers of datasets.

Region	Number of recipes			Average number of ingredient		
	Dataset 1	Dataset 2	Dataset 3	Dataset 1	Dataset 2	Dataset 3
Mediterranean	2214	256	231	8,29	10.69	8.60
Eastern Anatolia	1625	263	237	7,28	9.25	7.27
Aegean	1865	103	92	8,37	9.24	7.49
Southeastern Anatolia	1533	281	251	8,47	10.68	8.18
Central Anatolia	2687	248	234	8,29	9.35	7.07
Black Sea	1208	274	247	6,58	7.94	5.99
Marmara	434	63	62	7,38	9.54	7.22

and the number of saves or user ratings. This does not provide evidence to support the claim that foods with a higher number of common flavor molecules will be more appreciated. This finding aligns with the results of Kort et al.'s (2010) experimental study, in which they compared the liking scores of food pairings with the individual scores of the paired ingredients, and no relationship was observed with the number of common flavor compounds.

Later, the most frequently used and prominent materials in the regional cuisines are examined and given in Tables 4 and 5, and the materials that are more specific to Turkish cuisine are given in Fig. 1.

As the dominance of ingredients such as onion, butter, wheat flour, tomato and pepper paste, yogurt, etc. among the regions prevents us from observing the unique ingredients of those regions, the previously explained usage comparison index (UCI) was used to reveal them.

So for example, while dry purple basil's use is only 4.94% in Eastern Anatolia, UCI shows that this percentage is 3.1 times its use in all cuisines, and in fact, it's an important ingredient in the cuisine. The same applies to pomegranate syrup, pepper paste, and cumin for the Mediterranean region, corn flour, beans, and hazelnut for the Black Sea region, etc. So while the possibility of coming across these ingredients isn't as high as the ingredients in Table 4, when you come across pomegranate syrup or cumin in a Turkish recipe, it's much more likely to be a recipe from Mediterranean cuisine. On the other hand, considering the relatively small sizes of the samples (especially for the Marmara and Aegean regions), all the ingredients here may not be that characteristic of the region.

Finally, the third data set was used to calculate the FPI values of the regional cuisines given in Tables 6–8.

To investigate the H_3, H_4, and H_5 hypotheses, and Wilcoxon test was performed to examine whether the FPI values of the recipes in the regional cuisines differed significantly from the average FPI values calculated for the control cuisines, which are given in Table 6.

As a result of the Wilcoxon test, it was observed that the FPI values in each cuisine were significantly different from Control 1 and 2, except for Southeastern Anatolian cuisines for Control 1 and Aegean cuisines for Control 2. On the other hand, it was observed that the FPI values for any cuisine did not differ significantly from Control 3. In this case, while the H_3 and H_4 hypotheses were partially supported, the H_5 hypothesis was not. When the mean index differences are examined, it is understood that while positive food pairing is observed in Mediterranean and Southeastern Anatolian cuisines, negative food pairing is observed in other regional cuisines. As the Mediterranean and Southeast Anatolian are the regions where the influence of Arabic cuisine is most evident in Turkish cuisine (Yayla and Aktaş 2021), and previous studies show positive food pairings in Arabic cuisine, this seems comprehensible. In Al-Razgan et al. (2021), the food pairing hypothesis was tested in Arabic cuisine, and it was concluded that positive food pairing was observed. Similarly, positive food pairing was observed in another study examining the food pairing hypothesis in Jordanian, Palestinian, Syrian, and Lebanese cuisines (Issa et al., 2018). On the other hand, the remaining five regional cuisines have shown negative food pairings. This is also in line with the previous study showing negative food pairing behavior in

Table 4
The most frequently used ingredients in regional cuisine.

Mediterranean				Eastern Anatolia				Central Anatolia				Black Sea			
No	Ingredient	f	%	No	Ingredient	f	%	No	Ingredient	f	%	No	Ingredient	f	%
1	Onion	133	51.9	1	Wheat flour	142	53.99	1	Wheat flour	141	56.85	1	Wheat flour	139	50.73
2	Sunflower oil	105	41.02	2	Onion	118	44.87	2	Sunflower oil	119	47.98	2	Butter	120	43.80
3	Black pepper	100	39.06	3	Butter	117	44.49	3	Butter	107	43.15	3	Sunflower oil	117	42.70
4	Garlic	91	35.55	4	Sunflower oil	116	44.11	4	Onion	92	37.10	4	Onion	99	36.13
5	Tomato paste	91	35.55	5	Egg	88	33.46	5	Tomato paste	86	34.68	5	Chili pepper	62	22.63
6	Pepper paste	87	33.98	6	Chili pepper	84	31.94	6	Black pepper	76	30.65	6	Egg	61	22.26
7	Chili pepper	80	31.25	7	Yogurt	80	30.42	7	Egg	75	30.24	7	Tomato paste	59	21.53
8	Wheat flour	79	30.86	8	Tomato paste	80	30.42	8	Chili pepper	63	25.40	8	Black pepper	59	21.53
9	Olive oil	75	29.30	9	Black pepper	71	27.00	9	Milk	54	21.77	9	Yogurt	52	18.98
10	Cumin	74	28.91	10	Fine bulgur[a]	47	17.87	10	Sugar	48	19.35	10	Sugar	50	18.25

Aegean				Southeastern Anatolia				Marmara			
No	Ingredient	f	%	No	Ingredient	f	%	No	Ingredient	f	%
1	Wheat flour	54	52.43	1	Black pepper	145	51.60	1	Wheat flour	38	60.32
2	Sunflower oil	49	47.57	2	Onion	145	51.60	2	Sunflower oil	30	47.62
3	Onion	38	36.89	3	Sunflower oil	120	42.70	3	Black pepper	23	36.51
4	Black pepper	33	32.04	4	Chili pepper	112	39.86	4	Butter	22	34.92
5	Tomato paste	24	23.30	5	Tomato paste	100	35.59	5	Milk	21	33.33
6	Butter	23	22.33	6	Garlic	85	30.25	6	Onion	21	33.33
7	Tomatoes	23	22.33	7	Wheat flour	85	30.25	7	Egg	17	26.98
8	Sugar	21	20.39	8	Tomatoes	85	30.25	8	Sugar	16	25.40
9	Parsley	21	20.39	9	Parsley	78	27.76	9	Yogurt	14	22.22
10	Egg	21	20.39	10	Olive oil	72	25.62	10	Tomatoes	13	20.63

[a] Bulgur: It is the product obtained by cleaning, cooking, drying, and breaking the *wheat (Triticum durum, Triticum aestivum, Triticum monococcum, and Triticum dicoccon)* in accordance with the technique.

Table 5
Ingredients that stand out in regional cuisine.

Mediterranean					Eastern Anatolia					Central Anatolia					Black Sea				
No	Ingredient	f	%	UCI	No	Ingredient	f	%	UCI	No	Ingredient	f	%	UCI	No	Ingredient	f	%	UCI
1	Pomegranate syrup	22	8.59	2.78	1	Dry purple basil[b]	13	4.94	3.10	1	Dry tomato	4	1.61	2.35	1	Cornflour	22	8.03	4.11
2	Pepper paste	87	33.98	2.61	2	Lean ground meat	8	3.04	2.65	2	Long green peppers	16	6.45	1.99	2	Green beans	7	2.55	2.45
3	Cumin	74	28.91	2.44	3	Erishte[c]	8	3.04	2.46	3	Grape vinegar	3	1.21	1.65	3	Hazelnut	12	4.38	2.04
4	Dovme[a]	12	4.69	2.37	4	Grape	4	1.52	2.30	4	Chicken meat	7	2.82	1.58	4	Fresh yeast	28	10.22	1.82
5	Lemon juice	32	12.50	2.35	5	Fine bulgur	47	17.87	2.17	5	Dry yufka (phyllo)[d]	3	1.21	1.56	5	Collard greens	10	3.65	1.80

Aegean					Southeastern Anatolia					Marmara				
No	Ingredient	f	%	UCI	No	Ingredient	f	%	UCI	No	Ingredient	f	%	UCI
1	Poppy	9	8.74	3.60	1	Cinnamon	20	7.12	3.03	1	Chicken legs	4	6.35	3.48
2	Egg white	6	5.83	3.31	2	Isot pepper[e]	18	6.41	2.68	2	Kaymak[f]	3	4.76	3.47
3	Coconut	4	3.88	2.76	3	Eggplant	41	14.59	2.52	3	Breadcrumbs	2	3.17	2.99
4	Fresh onion	5	4.85	2.66	4	Allspice	17	6.05	2.45	4	Egg yolk	11	17.46	2.96
5	Bread	4	3.88	2.36	5	Fine bulgur	8	2.85	2.37	5	Tahini	6	9.52	2.76

UCI: The usage comparison index.
[a] Dovme: It is obtained from Anatolian hard wheat by boiling and pounding it in the traditional village method.
[b] Dry purple basil: an aromatic annual herb of the mint family, native to tropical Asia.
[c] Erishte: It is a kind of pasta obtained by cutting the dough, which is a mixture of flour, oil, and salt, with a knife in the form of thin sticks or squares.
[d] Dry yufka (phyllo).
[e] Isot pepper: It is a dried Turkish hot pepper from the *Capsicum annum* species grown in Şanlıurfa, Turkey.
[f] Kaymak: It is a cream product obtained by condensing the fat of milk.

southern European cuisines (Ahn et al., 2011).

Also, it was observed that the FPI values of any regional cuisine did not significantly differ from the Control 3 cuisines, which were created based on the ingredient usage frequencies in the regional cuisines. This finding seems to be compatible with previous studies (Jain et al., 2015) and shows that FPI values are largely due to ingredient usage frequencies.

Tables 7 and 8 show the top seven materials that contributed the most to positive and negative food pairings.

Note that this calculation had to be made with transformed ingredients, as explained in the methods section, in order to acquire FPI values. Therefore, for example, capsicum expresses ingredients such as chili pepper, red pepper flakes, and pepper paste; tomato includes tomato paste; wheat includes bulgur, etc. Also, while both frequency of use and the number of flavor compounds of an ingredient have an influence on this value, other ingredients used with the ingredient in the recipes can radically change its contribution index. This result, along with the previous ones, shows that the positive food pairing behavior of Mediterranean and Southeastern cuisines can be partially attributed to less frequent use of flour and more frequent use of pepper paste, chili pepper, and garlic.

Overall, while the local cuisines of Turkey generally show food pairing behaviors comparable to similar cuisines, it has been seen that this situation is largely due to the frequency of material use. Similar to our study, Jain et al. (2015) examined the local cuisines of India and found that each of the eight cuisines examined had negative food pairings. Similarly, Makinei et al. (2021) investigated Indian Assamese cuisine recipes and discovered a negative food pairing trend.

In this study, in addition to the randomly created kitchen, control kitchens were also established to serve as a comparison. These control kitchens maintained the categories and/or frequencies of food items. It was reported that the control kitchens, where the frequencies were preserved, yielded values similar to those of real kitchens. Thus, it appears that the frequency of ingredient usage is the most crucial factor determining the food pairing behavior of the kitchens. Also, correlation analysis hasn't shown a relationship between consumer liking (rating and saving) of the recipes and FPI values. Therefore, our proposed food pairing hypotheses were not supported. In a study by Kort et al. (2010) in which the food pairing hypothesis was tested experimentally, seven pureed ingredients were tasted and scored by blindfolded participants individually and in pairs. The food pairing hypothesis was not supported, as in our study, as the combinations with the highest volatile substance ratio in common were not the combinations with higher liking scores.

As this approach ignores other attributes of food and focuses solely on the number of shared flavor molecules, it fails to predict the success of food pairing and, therefore, consumer liking in the experimental studies. As a matter of fact, one of the important supporters of the food pairing hypothesis, Blumenthal, later acknowledged and expressed the shortcomings of the hypothesis as well (Blumenthal, 2010; Spence et al., 2017). As Spence and Youssef (2018) also pointed out, chefs often rely on gut instinct while preparing food instead of theory. In this case, the "success" of that current "*food pairing hypothesis*" can be attributed solely to encouraging chefs to try combinations they wouldn't normally attempt.

Arellano-Covarrubias et al. (2019) argue that focusing only on chemical components is lacking in food pairing studies and that cultural influences should also be considered. Taste perceptions in societies can show cultural differences. In this context, it is necessary to propose models of the food pairing hypothesis that take into account geographical, climatic, historical, ethnic, and cultural influences. Another study on food pairing found that the pairing of certain sauces with certain foodstuffs depended on cultures. It has been suggested that the reason for this is that some foods consumed in one country are not suitable in other countries with different cultures (Kim et al., 2018). Galmarini et al. (2017) contributed to food pairing, and a consumer

Fig. 1. Some of the prominent ingredients in regional cuisines
[1] Bulgur: It is the product obtained by cleaning, cooking, drying, and breaking the *wheat (Triticum durum, Triticum aestivum, Triticum monococcum, and Triticum dicoccon)* in accordance with the technique.
[2]Dovme: It is obtained from Anatolian hard wheat by boiling and pounding it in the traditional village method.
[3]Dry purple basil: an aromatic annual herb of the mint family, native to tropical Asia.
[4]Erishte: It is a kind of pasta obtained by cutting the dough, which is a mixture of flour, oil, and salt, with a knife in the form of thin sticks or squares.
[5]Dry yufka (phyllo): The dough prepared with wheat flour is rolled out in the form of phyllo and dried by baking it on a sheet of metal.
[6]Isot pepper: It is a dried Turkish hot pepper from the *Capsicum annuum* species grown in Şanlıurfa, Turkey.
[7]Kaymak: It is a cream product obtained by condensing the fat of milk. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 6
Wilcoxon test comparing original and control FPI Values.

Regional Cuisine	Control Group[a]	p value	Average of FPI (Original)	SD	Average of FPI (control)	Difference of Means
Mediterranean cuisine	Mediterranean vs Control 1	**0.008**	101.82	50.93	91.95	9.87
	Mediterranean Control 2	**<0.001**	101.82	50.93	77.33	24.49
	Mediterranean Control 3	0.937	101.82	50.93	101.24	0.58
Eastern Anatolian Cuisine	Eastern Anatolian Control 1	**<0.001**	70.25	50.20	92.34	-22.09
	Eastern Anatolian Control 2	**0.006**	70.25	50.20	77.09	-6.84
	Eastern Anatolian Control 3	0.758	70.25	50.20	68.62	1.64
Aegean Cuisine	Aegean Control 1	**<0.001**	69.24	48.74	93.12	-23.88
	Aegean Control 2	0.080	69.24	48.74	77.50	-8.26
	Aegean Control 3	0.219	69.24	48.74	73.99	-4.74
Southeast Anatolian Cuisine	Southeast Anatolian Control 1	0.152	97.00	54.29	91.76	5.23
	Southeast Anatolian Control 2	**<0.001**	97.00	54.29	77.58	19.41
	Southeast Anatolian Control 3	0.212	97.00	54.29	92.44	4.56
Central Anatolian Cuisine	Central Anatolian Control 1	**<0.001**	65.90	48.81	90.60	-24.70
	Central Anatolian Control 2	**<0.001**	65.90	48.81	76.52	-10.62
	Central Anatolian Control 3	0.987	65.90	48.81	64.05	1.86
Black Sea Cuisine	Black Sea Control 1	**<0.001**	63.18	50.09	91.75	-28.57
	Black Sea Control 2	**<0.001**	63.18	50.09	77.80	-14.62
	Black Sea Control 3	0.541	63.18	50.09	61.73	1.46
Marmara Cuisine	Marmara Control 1	**<0.001**	62.96	46.28	91.58	-28.63
	Marmara Control 2	**0.006**	62.96	46.28	80.21	-17.25
	Marmara Control 3	0.992	62.96	46.28	59.97	2.99

[a] Each original cuisine's FPI value was compared with their respective control groups.

panel defined as Temporal Dominance of Sensations (TDS), which includes the food cultures of the countries, was used. The TDS method is a sensory evaluation technique used to evaluate the temporal sequence of sensations experienced during the consumption of a food or beverage product. In this study, the effect of wine on cheese was examined in terms of sensory perception and taste with the TDS method. In this context, it can be argued that culture is an important component and variable in food pairing (Galmarini, 2020).

Ahn et al. (2011) utilized computational gastronomy in order to test the food pairing hypothesis, which later gave rise to other similar studies. This approach assumed that if the hypothesis is true, food recipes should have high levels of common flavor compounds among their

Table 7
Food ingredients that contribute positively to the FPI value.

	Name	Total	Mediterranean	Eastern Anatolia	Aegean	Southeastern Anatolia	Central Anatolia	Black Sea	Marmara
1	Capsicum	**7.78**	**9.85**	**7.10**	**5.99**	**9.71**	**7.09**	**6.05**	**7.05**
2	Tomato	**6.73**	**7.12**	**5.49**	**6.64**	**8.18**	**8.35**	**4.70**	**6.15**
3	Black pepper	**4.48**	**4.95**	**3.76**	**4.74**	**6.71**	**4.11**	**2.53**	**5.18**
4	Onion	**4.18**	**4.88**	**3.86**	**4.08**	**4.00**	**3.72**	**4.51**	**4.05**
5	Garlic	**2.23**	**2.80**	1.63	**2.03**	**3.04**	**2.33**	1.60	**1.54**
6	Wheat	**2.15**	2.27	**3.75**	1.10	2.52	**1.73**	1.28	0.62
7	Parsley	**2.06**	**3.19**	1.56	**3.00**	**3.11**	1.43	0.79	**1.53**
8	Rice	1.53	1.46	0.53	0.50	**2.97**	1.12	**2.01**	1.02
9	Mint	1.51	2.59	**1.74**	1.24	1.54	1.12	0.73	1.44
10	Potato	1.32	1.22	**1.73**	0.87	1.09	**1.73**	1.18	0.69
11	Lemon	1.29	**2.66**	0.82	**1.96**	1.73	0.89	0.27	0.77
12	Walnut	1.17	1.01	1.01	1.35	1.00	0.79	**2.04**	0.77
18	Corn	0.48	0.15	0.05	0.11	0.31	0.13	**1.94**	0.18
23	Bread	0.40	0.28	0.05	0.45	0.89	0.32	0.11	**1.65**

*Only ingredients with highest seven contribution index in one of the regions was included in the table and top seven ingredient in each cuisine is shown with **bold**.

Table 8
Food ingredients that contribute negatively to the FPI value.

	Name	Total	Mediterranean	Eastern Anatolia	Aegean	Southeastern Anatolia	Central Anatolia	Black Sea	Marmara
1	Sunflower Oil	**-11.29**	**-12.29**	**-10.26**	**-12.55**	**-12.37**	**-10.65**	**-10.92**	**-9.17**
2	Flour	**-6.80**	**-5.90**	**-9.03**	**-7.70**	**-3.70**	**-7.48**	**-7.32**	**-8.53**
3	Olive Oil	**-5.43**	**-10.00**	**-3.34**	**-6.97**	**-8.51**	**-2.11**	**-3.25**	**-2.77**
4	Beef	**-4.93**	**-5.00**	**-4.11**	**-3.38**	**-7.92**	**-5.22**	**-2.68**	**-5.92**
5	Yogurt	**-3.25**	**-2.93**	**-5.37**	**-3.96**	-1.81	**-2.58**	**-3.26**	**-3.61**
6	Sugar	**-2.89**	**-3.09**	**-1.88**	**-2.71**	-1.78	**-2.34**	**-5.51**	**-2.64**
7	Egg	**-1.54**	-1.14	**-1.73**	**-1.86**	**-1.89**	**-1.61**	**-1.58**	0.11
8	Lamb	-1.29	-1.26	-0.44	-0.54	**-2.97**	-1.16	-0.68	**-1.75**
9	Sumac	-1.13	**-3.64**	-0.42	0.05	**-1.92**	-0.26	-0.08	-0.61

*Only ingredients with highest seven contribution index in one of the regions was included in the table and top seven ingredient in each cuisine is shown with **bold**.

ingredients, as they are comprised of ingredients that complement each other. As a result of this study, some cuisines showed significantly higher (American and Western European) and some cuisines showed significantly lower (Southern European and East Asian) numbers of average common compounds than expected to be seen randomly. In later studies, these are called positive and negative food pairings (Al-Razgan et al., 2021; Goel and Bagler, 2022; Jain et al., 2015).

In addition, there are some deficiencies in computational gastronomy studies where this hypothesis is statistically tested. Firstly, the databases concerning aroma molecules significantly influence the results. For instance, Varshney et al. (2013) explored medieval European cuisine using two different flavor molecule datasets (Fenaroli and VCF), resulting in one dataset suggesting positive food pairing and the other indicating negative food pairing. Moreover, the current approach does not consider the quantities of aroma molecules in the ingredients or the quantities of the ingredients in the recipes.

4. Conclusion

In this study on Turkish local cuisines, we obtained values indicating positive food pairing behavior in two regions and negative food pairing behavior in five regions, and it was observed that this pattern was consistent with other cuisines that shared similarities with regional cuisines. However, it has also been noticed that the calculated FPI (Food Pairing Index) values are heavily influenced by the frequency of ingredient usage in the kitchen. Furthermore, no correlation was found between FPI values and ratings or the number of saves, which are expected to reflect users' liking for recipes or foods.

When considering previous findings and criticisms collectively, it becomes evident that the food pairing hypothesis and the current computational gastronomy approach have achieved only partial success. At this point, it seems necessary to improve the databases related to aroma molecules and develop theories that better explain the relationship between aroma molecules and taste, consumer preference, and food pairings. However, future research in this field may lead to the creation of models that account for more aspects of dishes, thereby enhancing our understanding of the complex nature of food.

Implications for gastronomy

The study contributes to gastronomy by highlighting the limitations of computational gastronomy, which involves pairing food components and flavor molecules that constitute the fundamental structure of cuisine. It is the first study on Turkish regional cuisines and food pairings. The research examines the food pairings of local cuisines, revealing positive food pairings in Mediterranean and Southeastern Anatolian cuisines, while negative pairings were observed in other regional cuisines. The results revealed that Food Pairing Index values were not significantly positively correlated with user scores, suggesting that the food pairing hypothesis cannot be fully supported.

Author statement

Murat Doğan: Definition, Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. Ahmet Hakan Değerli: Definition, Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that there is no conflict of interest.

Data availability

No data was used for the research described in the article.

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