PAIRING BEER AND FOOD IN SOCIAL MEDIA: IS IT AN IMAGE WORTH MORE THAN A THOUSAND WORDS?

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Declarations of interest: none

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ABSTRACT

Food pairing has been widely studied to understand the patterns that explain how people pair different foods and ingredients and, therefore, to obtain successful pairings and good recommendations for consumers. Social media has become a common way of exchanging information; therefore, we proposed to use it as a tool for exploring beer-food pairing and eating behavior. Twitter and Instagram were selected as they are among the most popular platforms. Although texts from Twitter could provide an accurate verbal description of consumer's food experiences, Instagram could offer the possibility of exploring the consumption context through images, leading to a better understanding of consumers' eating behavior, with a focus on food and beverage combinations. We hypothesize that images from Instagram will provide further information than texts from Twitter, regarding beer-food pairing and consumption context. A social media study was performed in Mexico comparing texts vs. images, selected from a one-year period, and manually classified through content analysis. Foods extracted from images and texts were categorized into frequencies and analyzed using multiple correspondence analysis (MCA) and hierarchical clustering (AHC). MCA showed the most frequently mentioned foods paired with beer for each platform. Data extracted from images and texts about consumption context was also analyzed and categorized into frequencies according to several themes: consumption behavior, type of consumption, way of beer consumption, place of consumption, and consumption occasion. Data extracted from the two platforms was compared by using a chi-square test per theme. Several differences were found, depending on the social media platform, texts being the one with less extracted and meaningful information. In general, while texts provided less extracted and meaningful information, images offered more details regarding beer-food pairing and context of consumption, the same as beer information such as type, color, brand, and style. Overall, images gave more information on beer-food pairing compared to texts. The methods and results from this paper could be applied by culinary professionals, sommeliers, and researchers in the gastronomy and food and hospitality areas.

Keywords: Food pairing, Context of consumption, Beer, Social media, Instagram, Twitter.

1. Introduction

Food pairing has been studied from different disciplines, such as gastronomy, sensory science, and history, to create new successful food and meal combinations and understand why people combine specific food and beverages. According to Paulsen et al. (2015), good pairing recommendations could be crucial for the success of foods, and beverages; additionally, Scander et al. (2018) stated that understanding the mechanisms behind beverage choice in different settings and cultural situations, and lifestyle backgrounds are needed to describe the intake patterns. Therefore, the study of social media could represent a valuable tool for exploring consumer food behavior, from which successful food and meals- beverage pairings could be identified.

Social media is one of the most accessible tools for sharing information, its popularity has increased a lot this past decade. Several studies reported that the use of this tool is now an integral part of the lives of many people, where consumers can easily gather information on which to base some of their decisions (Casaló et al., 2018), for example, helping consumers to decide what to buy or just to know more about certain products or brands (Powers et al., 2012). According to Mangold and Faulds (2009), consumers are turning away from traditional media such as television, magazines, and newspapers, which makes social media a valuable tool in consumer research.

Across different social media platforms, two of the most popular are Instagram and Twitter. According to Alexa's ranking web sites in Mexico (Alexa, 2021), which categorize by the number of visitors and site views, Twitter is positioned in 18th place while Instagram is in 15th place. These platforms use mainly text to share information in the case of Twitter and images for Instagram. Nowadays, and with the constant growth of social media use, researchers should create and apply new techniques involving social media analysis that could be used to better retrieve spontaneous responses of the consumers, in real-life settings (Vidal et al., 2015).

1.1 Twitter and Instagram

The Twitter platform was launched in July 2006, and by 2018, the platform already hosted 326 million active users, all over the world. This micro-blogging service encourage it users to publish anything that they need and have to say, as they claimed on their own web site: "Twitter is what's happening in the world and what people are talking about right now" (Twitter, 2021). As well as other micro-blogging web sites, Twitter has an important effect on early product adoption because of the immediate dissemination of post purchase quality evaluations (Hennig- Thurau et al., 2015).

Extensive research about food has been carried out using Twitter, such as describing Twitter publications regarding different eating situations (Vidal et al., 2015), influence of environment on food choices (Chen and Xining, 2014) and information sharing (Platania and Spadoni, 2018). In general, this platform could be a good tool for gathering information regarding context and additionally, the limit of characters that can be written in a tweet (280 characters) also facilitate the interpretation of the data (Zhou and Chen, 2014). The platform allows to add images, videos, and emoticons; however, it was originally created to connect and communicate people through texts, and it is still the main source of information in the tweets.

On the other hand, Instagram is a social media platform launched in 2006 (Instagram-press, 2019). This platform that has increased in popularity over the last years, has more than 1000 million active users (Wearesocial, 2019). According to the app developers, the main objective of Instagram is "to connect you with the people and things that matter to you" (Instagram, 2021). Instagram users are encouraged to post images for each individual or social activity that they are performing, such as daily activities, exercise, travel, parties, work, and food consumption, being this last the one that usually attracts the attention of users. In other words, it is an image-based social media platform that as a conventional wisdom, is mostly used for self-promoting and social networking with friends (Hu et al., 2014).

In their study, Hu et al. (2014) categorized a sample of Instagram images and found out that the *food* category contributed to more than 10% of the published images, only below *selfies (24.2%), friends (22.4%),* and *activities (15%)* categories. Taking pictures of food has become widespread among consumers and raises several questions, such as what kind of food images are posted (including the most popular food-beverage combinations) and which are the consumer's motivations to post them. Sester et al. (2013) stated, that answering all the questions implies the observation of the context of a specific situation of food consumption. In the present research, texts from Twitter and images from Instagram are used as research tools to explore the context of consumption of users.

1.2 Context of consumption and food pairing

The consumption context, according to Meiselman (2006), is defined as the physical, social, and situational conditions in which consumers eat food and beverages. Context of consumption is difficult to observe within traditional consumer tests due to different aspects, in which time investment, cost, recruitment of representative samples, and the simulation of a natural environment are the main issues.

Additionally, it is well reported that people do not “act normally” when they are aware of being observed (or being interviewed) and consequently, the results could be biased. In fact, people could be more honest when interacting with a computer rather than with a human interviewer (Gnambs and Kaspar, 2015). So, when venturing into new techniques and tools for gathering information, such as social media, researchers could observe real food behavior from people in their natural context. Social media could offer instantaneous access to a large and representative consumer sample, as Meiselman (2013) states, this aspect meets a real need for consumer science research.

Considering this social phenomenon, using social media as a source of information could be a useful tool when exploring consumer behavior in real-life situations. According to Galiñanes et al. (2019), almost all the research on human eating behavior has been focused on food items instead of food combinations, which could contribute to misleading results. That is the case of food pairing, which has been a popular topic in the last decades, in which researchers have been looking for a pattern that could explain how people pair different ingredients, and consequently to find successful pairings for consumers (Ahn et al., 2011; Varshney et al., 2013).

Food Pairing Theory states that the more aromatic compounds two foods have in common, the better they taste together (Klepper, 2011). However, it is complicated to determine universal guidelines for good pairings due to the complex nature of the sensory interactions between food and beverages (Paulsen, 2015). Therefore, volatile compatibility is not the only answer to good pairings (Galmarini, 2020). In general, food pairing has been widely studied when pairing wine and cheese (King and Cliff, 2005; Bastian et al., 2010; Harrington and Seo, 2015), chocolate with different beverages (Donadini et al., 2012), and the pairings of other foods such as olive oil (Cerretani et al., 2007) or banana (Traynor et al., 2013). However, in the case of beer food pairing, little research can be found (Donadini et al., 2008; Donadini et al., 2013; Eschevins et al., 2019; Paulsen et al., 2015; Martínez et al., 2017).

Galmarini (2020) stated that food-pairing field needs a consumer-oriented approach to better understand what makes a good combination, and despite food pairing had been studied by using traditional sensory methodologies, the usage of different social media has not been explored, which arises an opportunity to gather beer food pairing information through images and texts. On our previous paper entitled “Connecting flavors in social media: A cross-cultural study with beer pairing” (Arellano-Covarrubias, A.; Gómez-Corona, C.; Varela, P., & Escalona-Buendía, H.B., 2019) we accessed the structure of food pairing for beer through the analysis of social media platforms and mainstream data in different countries. Results showed that the platforms with a more substantial number of mentions were Twitter and Instagram. Facebook did not show high number of mentions due to the characteristics of the platform, in which users usually made private their profiles so only their “friends” could access to their publications, contrarily from Instagram and Twitter in which the profiles, in general, are public so anyone could access to the user’s information/publications. In the present study, we research and compare the information extracted from texts versus images (from Twitter and Instagram, respectively), to understand which one provides a better understanding of beer-food pairing and more information about context of consumption. We hypothesize that, in general, texts from Twitter are less informative than images from Instagram in the case of beer food pairing and context of consumption.

2. Materials & methods

The data for the present study was extracted using Synthesio® (Synthesio® social media listening platform, 2018). Twitter and Instagram publications related to beer and flavor/food combinations were selected from a year’s base (July 18, 2016, to July 18, 2017) of our previous study. In this previous research, all publications were searched from a list of sixty-five popular flavors/foods and words related to beer (e.g., beer, beers) and associated with food consumption words (e.g., flavor, food, eat, food combination, etc.). As a result, all kinds of posts from social media and mainstream data (related to beer/food combinations) were extracted.

In the present research, to test the proposed methodological approach, the analysis of texts (from Twitter) and images (from Instagram) was limited to Mexico, from January to December 2018. For further information about the extraction procedure of the Twitter and Instagram data, see Arellano-Covarrubias et al. (2019).

2.1 Data selection

From the Twitter and Instagram social media database, 200 tweets and 200 images from Instagram were extracted, all related to beer and foods. According to Hough et al. (2006), the minimal number of consumers necessary for sensory acceptability studies is 112, as we are dealing with consumers publishing their food consumption, a higher number was selected for this purpose. For each randomly selected social media publication, we accessed to the user profile who published, and the post was discarded if it comes from companies and/or publicity to avoid data bias, so that only the information published by consumers was selected. Re-tweet or re-post of images were also discarded (Vidal et al., 2015). The randomized selection was performed until an original publication was chosen, and achieved the target number of 200 Instagram posts, and 200 tweets. Only 13% of the selected tweets contained an image. For the purpose of this research only the text of the tweets was analyzed, and only images from Instagram.

2.2 Content analysis

Each text from the tweets and Instagram image related to beer were manually coded using qualitative content analysis (inductive analysis) (Thomas, D.R., 2006). For understanding purposes, we will use “text” when referring to the text from the tweets and “images” to the pictures from Instagram. To report the user characteristics, the gender information was extracted, when available, by accessing to the public profile of the user.

For beer-food pairing extraction, each text was analyzed and extracted all the food associated with beer, where foods are represented by the food names mentioned in the publications. In the case of the images, we accessed the original image and extracted all foods, also related to beer, that could be seen in the picture. The frequency of occurrence was calculated for all foods and a contingency table from both texts and images was created. For a better understanding of this research, we will use the word “food” to refer to both food names extracted from texts and to the foods extracted from analyzing images.

Regarding beer context of consumption, all images and texts were analyzed and classified according to consumption behavior themes and subthemes. The election of themes and subthemes were performed by one researcher, and then agreed by two additional researchers, until a consensus was achieved. To perform the classification of the texts and images, each publication was assigned to a *subtheme* of each theme according to the content analysis, and a percentage of occurrence table was created. Additional information from texts and images, such as hashtags, text descriptions, or image titles, was also considered to perform the classification.

For both texts and images, whether the publication belonged to a negative, neutral, or positive consumption experience was registered. This classification was performed according to the context of the post and the words used in the publications, in which some feelings (or words related) such as happiness, excitement or pleasant, were classified as “positive”. In the case of complaints, bad moods, or sadness, the posts were classified as “negative”, and finally, “neutral” classification included all feelings that could not fit in positive or negative (indifference, lack of sympathy). If the intention of the post was not clearly identified, then it was classified as “neutral”.

Finally, beer information (type, color, brand, and beer style) was also extracted if it could be identified in the text or seen in the image.

2.3 Data analysis

Gender was categorized in a contingency table for texts and images and each category was compared through multiple z-proportions tests. To obtain the beer pairings, a frequency table of foods was built for both texts and images, categorizing the food names that were mentioned in the case of texts, or seen in an image. Percentage of occurrence of each food per platform (text and image) was calculated, and food with less than 1% of occurrence was discarded to avoid low-frequency data. For each food frequency table, a multiple correspondence analysis (MCA) was performed followed by an agglomerative hierarchical clustering (AHC) with Ward algorithm on the first two factors of the MCA, and where the clusters were defined by the abrupt change in the similarity level (Lebart, 2006). An RV coefficient analysis was performed to the first two factors between both MCA to test differences within the coordinates.

All information regarding beer context of consumption was arranged in a percentage of occurrence table for themes and subthemes. Chi-square tests were applied to compare each theme within platforms, and multiple z-proportion tests were performed to test specific differences within subthemes.

Consumption experience (positive, negative, or neutral) and beer information (type and color), were categorized in a contingency table for both platforms and each category was compared through chi-square test, followed by multiple z-proportions tests within subcategories. Finally, regarding beer brands and styles, the percentages of occurrence were calculated.

All statistical analyses were performed with XLSTAT software version 2012.5.02 (Addinsoft, 2019).

3. Results

The results obtained from the information extracted from texts and images will be interpreted in two parts: beer food pairing and context of consumption. The first one focuses on the differences in the available information from images versus texts regarding food pairing with beer, while the second part provides an overview of the consumption context that could be extracted.

From the user's characteristics, the gender was categorized in a contingency table. In this research, the results of multiple z-proportions tests for gender (Table 1) showed no significant difference within platforms; however, considering that between 17.5% and 20% of the gender for each platform was unknown, a conclusion about gender behavior cannot be done.

Table 1

Chi-square and z-proportion test results for gender. Values shown are percentages.

Category	Subcategory	Twitter	Instagram	P-value
Gender	Both gender	0	**1**	1.000
	Female	31.5	**39**	0.142
	Male	**48.5**	42.5	0.269
	Unknown	**20**	17.5	0.608

Bold numbers indicate the higher percentage of occurrence for the respective platform.

3.1 Beer food pairing

For beer-food pairings, the frequency of occurrence was calculated for each food identified from texts and images. Some of the original translated texts are as follows, where the extracted food names and the type of beer are in bold letters: “For a hangover, I recommend a **Corona beer** in a frosted glass with ice, **salt**, **lime** and ready!”; “In summary: **coffee**, **whiskey**, **pizza**, **beer**, and a long series of memories, but always with good company”.

In the case of images, all foods combined with beer that could be seen were extracted; for example, from Figure 1a, chili and lime were extracted, in Figure 1b, lime, chili, and mezcal were extracted, and, in Figure 1c, orange, peanut, jicama, and chili were extracted. Figure 1 includes the author’s pictures recreation for illustrative purposes; the original images from the users are not shown due to privacy issues.

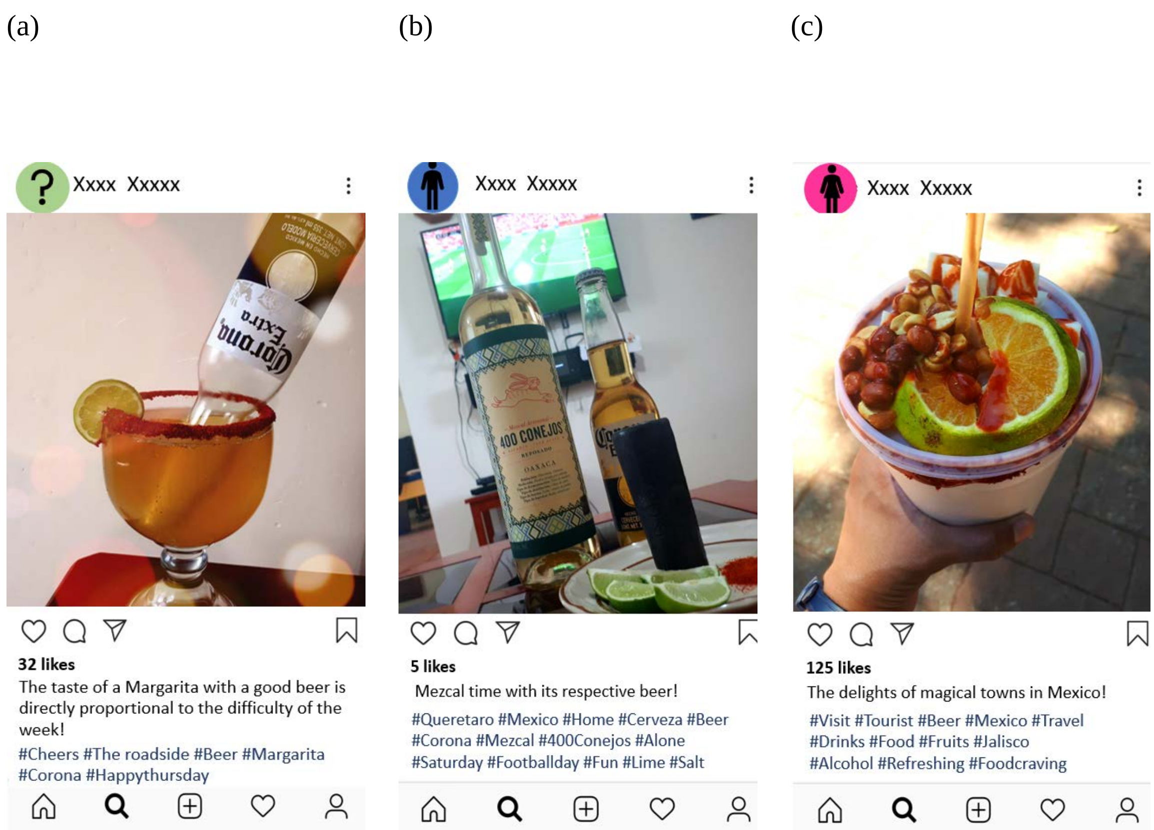


Fig.1 Images created by the authors. Original publications are not shown to protect the privacy of consumers. The images' comments are original; however, the identities of the consumers remain unknown.

The data retrieved from the content analysis of texts and images provided 85 foods that users paired with beer. These foods were arranged in a frequency table of food per platform, and the percentage of occurrence was calculated by using the number of total food mentions in each platform (for images: 1154, for texts 557). Finally, forty-nine foods with less than 1% of occurrence for both platforms were discarded, and a new table was created for the remaining 36 foods (Table 2), representing the most popular foods that consumers combined with beer. In general, images contained a higher number of mentions, except for salty snacks, pizza, coffee, wine, and oats, which had higher frequencies of occurrence for texts.

Table 2

Frequency of occurrence for foods per platform.

Food	Texts	Images
Chili	35	**136**
Salt	18	**92**
Lime	37	**91**

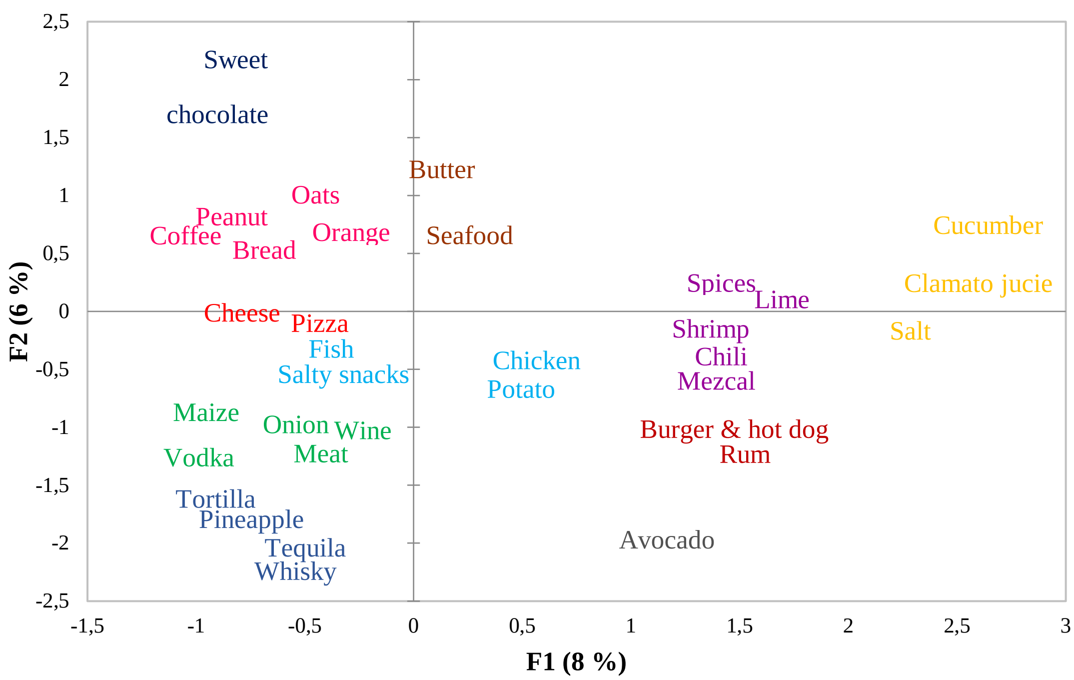
Spices	17	**90**
Cheese	39	**64**
Meat	28	**60**
Bread	26	**49**
Tortilla	18	**48**
Onion	7	**41**
Mezcal	6	**33**
Tequila	13	**28**
Potato	10	**27**
Tomato	0	**24**
Avocado	3	**22**
Peanut	5	**18**
Salty snacks	**35**	14
Shrimp	3	**13**
Cucumber	2	**13**
Pizza	**21**	8
Coffee	**16**	5
Wine	**13**	3
Oats	**7**	0
Clamato juice (tomato & clam)	11	**19**
Chicken	**25**	16
Orange	6	**14**
Chocolate	**18**	11
Burger & hot dog	6	**11**
Fish	10	**11**
Seafood	8	**10**
Pineapple	6	**9**
Maize	7	**8**
Butter	7	**8**
Sweet	7	7
Vodka	**9**	2
Rum	**7**	1
Whisky	**6**	1

Bold numbers indicate the higher frequency of occurrence for the respective platform. (n texts= 200; n images =200)

With the 36 foods with more than 1% of occurrence for each platform, a multiple correspondence analysis (MCA) was performed to create beer-food pairings maps. The RV coefficient between the first two factors of both MCA showed that the coordinates of the maps are not similar (RV=0.126; *p-value*=0.067), and consequently, that the MCA structures are also different. Fig. 2 shows the food-pairing maps, considering the first two factors of the MCA. The results of the hierarchical cluster analysis (HCA) showed eleven clusters for texts and eight clusters for images, which illustrates the beer-food pairing information retrieved from each platform.

Some patterns within the clusters from both food-pairing maps were identified: lime, chili, and spices were grouped in the same cluster on both platforms. Also, pizza and cheese were clustered together, and additionally for images, pineapple was also included in the same cluster. Regarding texts information, no other patterns could be found, but in the case of images, all seafood was clustered together (fish, shrimp, seafood), while in another cluster, all vegetables were grouped together, with the potato food exception, which was clustered along with butter, burger, and hot dogs. Additionally for images, wine, bread, and cheese were grouped in the same cluster; and finally, meat and chicken were also grouped together. In general, food pairings that combined well with beer could be extracted from the clusters of each food-pairing map.

(a)



(b)

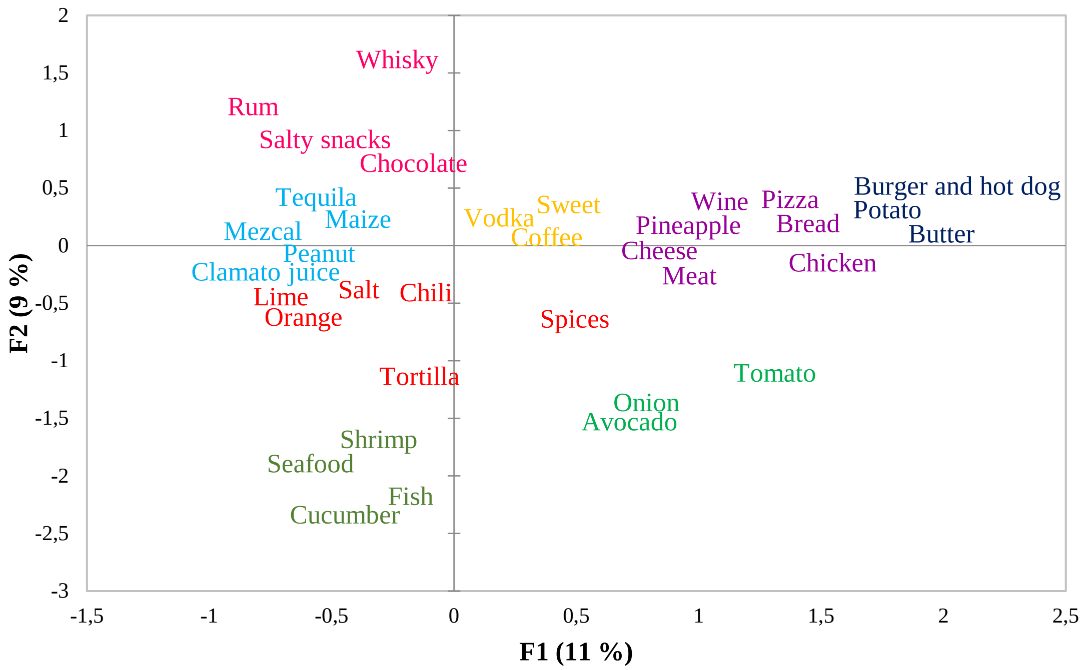


Fig.2 Food pairing maps for (a) texts and (b) images. The hierarchical clustering of each MCA map is represented by similar colors, in which foods were clustered in 11 groups (a) and 8 groups (b).

3.2 Context of consumption

Regarding the beer context of consumption, several themes and subthemes were selected after the author's consensus. The **themes** and *subthemes* were **consumption behavior** (subthemes: *consuming, craving, making plans, past consumption, and other/unknown*), **type of consumption** (subthemes: *individual, social, and unknown*), **way of beer consumption** (subthemes: *can, bottle, glass, and other/unknown*), **place of consumption** (subthemes: *restaurant/bar, home, other (beach/office), and unknown*) and **consumption occasion** (subthemes: *celebration, travel, frequent consumption, and other/unknown).*

Each image and text were categorized in one subtheme of each theme. For example, in Figure 1b, the user is consuming at the time of the post due to the title of the picture: "Mezcal time with its respective beer!". Also, the user is drinking beer directly from the bottle in a place which seems to be home (#Home); the hashtags "#Saturday, #Footballday" may suggest that the user usually consumes these products on Saturdays while watching TV, and behind the beer, we could see the place of consumption (#home).

Regarding texts, the extraction of the information was performed in a similar process but extracting the written information that users posted. An example of the extracted text is as follows: “I will sit in the armchair at home, eating nachos with cheese, and drinking beer!”. In this case, the user is making plans, presumably for individual consumption (“I”) while staying at home. More information could not be identified.

Context of consumption data showed differences in chi-square tests for all themes, while z-proportion tests showed differences in almost all subthemes, except for home and other (theme: place of consumption) and celebration and frequent (theme: consumption occasion) (Table 3).

Table 3

Chi-square and z-proportion test results for context of consumption. Values show the percentage of occurrence of subthemes identified through content analysis for images and texts

Theme	Subtheme	Texts (%)	Images (%)	P-value
Consumption behavior ($\chi^2_{(4,400)}$ = 79.534, $p<0.0001$)	**Consuming**	25	**67.5**	<0.0001
	Craving	**9**	0	<0.0001
	Making plans	**11**	3.5	0.006
	Past consumption	**20.5**	11.5	0.016
	Other/unknown	**34.5**	17.5	0.0004
Type of consumption ($\chi^2_{(2,400)}$ =27.143, $p<0.0001$)	**Individual**	**56**	40	0.002
	Social	21	**46**	<0.0001
	Unknown	**23**	14	0.028
Way of beer consumption ($\chi^2_{(3,412)}$ = 325.590, $p<0.0001$)	**Can**	0.5	**5.7**	0.0049
	Bottle	0.5	**44.8**	<0.0001
	Glass	10	**48.1**	<0.0001
	Other/unknown	**89**	1.4	<0.0001
Place of consumption ($\chi^2_{(3,400)}$ = 115.415, $p<0.0001$)	**Restaurant/Bar**	16	**62.5**	<0.0001
	Home	18	13.5	0.271
	Other (Sport games, Beach, Office)	4	8.5	0.097
	Unknown	**62**	15.5	<0.0001
Consumption occasion ($\chi^2_{(3,400)}$ = 32.998, $p<0.0001$)	Celebration	5.5	8.5	0.340
	Travel	3	**20.5**	<0.0001
	Frequent	39.5	34.5	0.365
	Other/unknown	**52**	36.5	0.002

Results of chi-square tests are shown for the respective theme. For z-proportions tests results, bold letters indicate the subthemes that were significantly different within platforms, while bold numbers indicate the higher percentage of occurrence for the respective platform. (n=200 for all themes for each platform, except for “way of beer consumption” theme for images, which n= 212 due to images showing more than one way of drinking beer).

Regarding the differences in beer consumption behavior theme, images showed more information when people were consuming at the present time (consuming), while for texts, most of the consumption behavior was unknown, while “craving”, “making plans”, and “past consumption” were found in lower quantities. In the case of the type of consumption theme from images, information about social consumption was obtained (e.g., “*Mezcal tastes better with a beer and good company*”), in which users mostly share images of spending time with friends, partners, or family. For texts, only individual consumption could be identified (e.g., *“My diet today: cake and coffee, cheese snack, beer, peanuts and a cigar*”), as the posts were mainly referred to the user’s consumption.

For the way of beer consumption theme in images, it was able to identify if the users consume beer from a can, bottle, or glass, while for texts, it was unable to identify the way of consumption in most of the posts. Regarding the place of consumption for images users, most of them publish images while consuming beer in restaurants/bars, while for texts, the place from which people are posting is unknown. Regarding the consumption occasion theme, there was no significant difference for frequent consumption within platforms; however, image users share more information when traveling. Additionally, for text users, the highest percentage of occurrence for the consumption occasion was unknown (e.g., “*My tacos with guacamole, beer, tequila and whisky*”; “*Chicken wings, onion rings and beer, delicious!”).*

Experience (positive, negative, or neutral) and beer information (type and color) were categorized in a contingency table, and each category was compared through a chi-square test (Table 4). Experience, beer type, and beer color categories showed significant differences, and to test specific differences within platforms, several z-proportions tests were performed for each subcategory. For the experience category, significant differences were found in all subcategories where images users posted a higher percentage of publications with a positive experience when compared to texts, and texts had higher neutral and negative experiences than images; however, on both platforms, the percentages for positive experiences were higher than the neutral or negative ones.

For beer type, significant differences were found for industrial and unknown types of beer, where images users had the highest percentage of industrial beer consumption, while for texts, the highest consumption of beer type is unknown. For beer color, significant differences were found for blond, dark, two or more colors, and unknown color, in which images users obtained the highest percentage of blond, dark, and two or more beer colors, while for texts, the highest percentage was for unknown beer color.

Table 4

Chi-square and z-proportion test results for additional information. Values shown are percentages.

Category	Subcategory	Twitter (%)	Instagram (%)	P-value
Experience ($\chi^2_{(2,400)}$ =19.154, *p<0.0001*)	**Positive**	72.5	**89**	<0.0001
	Neutral	**18**	9	0.012
	Negative	**9.5**	2	0.002
Beer type ($\chi^2_{(3,400)}$ =113.184, *p<0.0001*)	Craft	9	14	0.157
	Industrial	12.5	**58**	<0.0001
	Both	0	1	0.477
	Unknown	**78.5**	27	<0.0001
Beer color ($\chi^2_{(5,400)}$ =179.597, *p<0.0001*)	Amber	1.5	3	0.500
	Blond	11	**53.5**	<0.0001
	Dark	9.5	**26**	<0.0001
	Two or more	0.5	**5**	0.014
	Other	0	1	0.477
	Unknown	**77.5**	11.5	<0.0001

Results of chi-square tests are shown for the respective category. For z-proportions tests results, bold letters indicate the subcategories that were significantly different, while bold numbers indicate the higher percentage of occurrence for the respective platform.

Regarding beer brand and style, images provided, in general, more information than texts. In the case of beer brand, 43 brands were identified from images and only 18 from texts; however, the highest percentage of occurrence for both platforms was for an unknown brand (81% for texts versus 28% for images). In the case of beer style, 14 styles from images and only 11 from texts were identified. The highest percentage of occurrence on texts belonged to an unknown style (80%), and it was followed by Pilsner beer with 8.5% occurrence. For beer styles for images, only 31% occurrence belonged to an unknown style, while the highest percentage (44.5%) was identified as Pilsner beer. Table 5 shows the different brands and styles that were identified from both platforms.

Table 5

Beer brands and styles identified from texts and images. Values shown are percentages.

Beer brands				Beer styles			
Texts (%)		Images (%)		Texts (%)		Images (%)	
Bluemoon	0.5	Affligem	0.5	Bock	0.5	Altbier Imperial	0.5
Calavera	0.5	Allende	0.5	India Pale Ale	1.0	American Pale Ale	1.0
Corona	6.5	Allende	0.5	Lager	1.0	Belgian Dubbel	0.5
Dirty Bastard	0.5	Becerro	1.0	Multiple styles	0.5	English Brown	0.5
Guinness	1.0	Berber	0.5	Pilsner	8.5	Imperial Stout	0.5
Heineken	1.5	Bocanegra	0.5	Porter	1.5	India Pale Ale	0.5
Házmela Rusa	0.5	Bohemia	1.0	Scotch Ale	0.5	Kölsch	0.5

Indio	0.5	Bud Light	0.5	Stout	3.0	Lambic	1.0
Minerva	3.0	Budweiser	0.5	Tequila Ale	1.0	Multiple styles	4.5
Mocachela	0.5	Corona	22.5	**Unknown style**	**80.0**	Munich	2.5
Modelo	0.5	Cucapá	0.5	Vienna	2.0	**Pilsner**	**44.5**
Multiple brands	0.5	Foca Parlante	0.5	Witbier	0.5	Porter	0.5
Noche buena	0.5	Fortuna	0.5			Stout	4.0
Patito	0.5	Heineken	4.0			Unknown style	31.0
Sierra Nevada	0.5	Honey Pale Ale	0.5			Vienna	7.5
Unknown brand	**81.0**	Házmela Rusa	0.5				
Victoria	1.0	Indio	2.0				
XX	0.5	La Bestia	0.5				
		Lindemans	1.0				
		Mezcalito Cococó	0.5				
		Michelob Ultra	1.5				
		Miller High Life	1.0				
		Minerva	2.0				
		Modelo	2.5				
		Modelo	0.5				
		Monolito	0.5				
		Multiple brands	5.5				
		Negra Modelo	2.0				
		Negra Modelo	0.5				
		Pacífico	2.0				
		Pulpo	0.5				
		Santta	0.5				
		Sol	1.0				
		Stella Artois	1.0				
		Tecate	2.0				
		Tecate	0.5				
		Tempus doble malta	0.5				
		Unknown brand	**28.0**				
		Victoria	2.5				
		Vida Latina	0.5				
		Wasumara	0.5				
		XX	5.5				
		Young's Double Chocolate	0.5				

Bold letters and numbers indicate the highest percentage of occurrence of beer brand and style for each platform

4. Discussion

The discussion is divided into three sections. The first one focuses on beer-food pairing information, while the second one focuses on the differences in the available information of the consumption context from texts and images. Finally, a short discussion section comparing image and text is added to highlight the importance of exploring both platforms as an information source of food-beverage pairing.

In this research, gender was no significant different within platforms. According to wearesocial (2019), the percentage of active women users for image platform (Instagram) is higher than active men users (women: 55%; men: 45%), while for text platform (Twitter), the percentage of active women users is lower than that of men (women: 35%; men: 65%). The results of multiple z-proportions tests showed that there was no significant difference, suggesting that both women and men post about beer to the same extent within platforms (and possibly also consume equally).

4.1 Beer food pairing

Table 2 showed the frequency of occurrence of foods that were combined with beer. The higher frequency of occurrence of foods extracted from images could be due that the main objectives of the platforms' usage are also different; while texts (Twitter) seem to be an opinion platform, images (Instagram) is for sharing experiences (Twitter, 2019; Instagram, 2019), which could have a direct impact on what kind of information people publish. Furthermore, the amount of registered information could reflect the data extraction methodology, from which the graphical characters such as emoticons, pictures, and videos were not considered for the analysis, in the scope of comparing the information for beer-food pairing from only texts versus images.

Although images had more mentions for most of the foods, chili, salt, and lime were frequently mentioned on both platforms combined with beer, and in accordance with our previous research, lime and chili had more extracted mentions for Mexico (Arellano et al., 2019). These similar results reflect how culture strongly influences beer-food pairing within the Mexican population. According to Lo Monaco and Bonetto (2019), all food norms and practices are transmitted between individuals and across generations over time, which could be the reason why some foods, such as chili, have been popular among Mexican consumers across generations. According to Spence (2018), chili occurrence has been widespread across many of the world's cuisines. Specifically for Mexico, Rozin (1990) and Katz (2009) stated that chili is the main characteristic of Mexican cuisine, and as expected, it could be reflected in their alcoholic beverage' consumption. In this sense, chili, salt, and lime foods could be part of the Mexican gastronomic identity, which according to Harrington (2005a), is a concept that arises because of environmental and cultural elements. A reflection of this behavior is the vast number of both images and texts of users that consumed "Micheladas", which are defined (with some variants according to specific regions in Mexico) as beer frosted with lime, salt, and chili, and which is widely known and consumed among Mexican people.

The main findings regarding alcoholic beverages were that Mezcal and Tequila, which are characteristics products of Mexico, were identified more frequently on images than texts. Wine was more frequently identified on texts than images, despite the low sale of this beverage in Mexico (and consequently a low consumption), where until 2013, the sales of wine were only 11.11% of total sales of beer, in millions of liters (Euromonitor, 2014). However, even though wine is not a very popular beverage among Mexican people, it has been reported a growth in their consumption in Mexico (Euromonitor, 2014).

From both food and beverage maps, the clusters from texts were less informative than the clusters from images. Within the patterns, pizza and cheese were joined in the same cluster on both platforms, and additionally for images, pineapple was also included in the same cluster; in this line, Donadini et al. (2008) mentioned that pizza is compatible with beer. For images, some foods were clustered by categories, such as seafood and vegetables. Finally for images, wine, bread, and cheese were grouped together, and despite wine and cheese are not commonly paired with beer, they are widely accepted to consume together (Harrington & Hammond, 2005b; Harrington, 2008; Bastian et al., 2010; Harrington et al., 2010). So, in general, the food and beverage maps from images provided the greatest amount of information and a more meaningful interpretation regarding the combination of foods with beer.

4.2 Context of consumption

All information about the context of consumption and eating behavior was extracted from images and texts. According to the results, and despite text users were classified as sharing individual consumptions, some research has stated that Twitter users gratified the need to connect with other people (Chen, 2011). On the other hand, images seem to match with social consumption, and according to Thomé et al. (2017), this social interaction is perceived as a guide for beer consumption, that could shape consumer behavior and actual purchase/brand choice. Therefore, social circumstances seem to be highly relevant in how we consume our food or which food we decide to consume (Abbar et al., 2015).

For the way of beer consumption theme in images, users share pictures of drinking beer in a glass or directly from the bottle, while for texts, users do not specify the way of drinking, which could be due to the limit of characters for text, in which users should communicate with shorter phrases. Regarding the place of consumption, most of the images represented a consumption of beer in restaurants/bars, in line with Lee et al. (2015), who stated that image platform (Instagram) users record their daily events and traces (e.g., trips), creating a personal cyber documentary through fancy photos. In the case of the consumption occasion theme, there was no significant difference for celebration and frequent consumption within platforms, which agrees with Java et al. (2007), who found that daily routine posts are among the most common uses of Twitter.

In the case of beer information for texts, it was challenging to identify all information about type and color, while for images, in almost all posts, the information could be categorized with industrial and blond and dark beer having higher percentages of occurrences. In general, we could infer that consumers that posted images are (mostly) industrial beer consumers who like blond and dark beers. However, given that texts do not give more information to clarify which products the users consume, we cannot discuss it in greater depth.

Regarding beer brand and style, images provided an advantage over texts. It is a fact that not in all images the users described the type of beer that they were drinking, but if the beer brand could be identified in the image, the additional information was investigated in the official websites of the products. In contrast, if some beer information was not given for texts, then all information remained unknown. In general, more beer brands and styles were identified from images than texts; Corona beer was the second brand with a higher percentage of occurrence for both text and image platforms. Gómez-Corona et al. (2016), in their research on habits of beer consumption in Mexico, reported Corona beer as the most frequently consumed beer brand; this popularity of Corona beer on social media could be attributable to the fact that it is a leading brand of alcoholic beverage in the national market (Grupo Modelo, 2019).

4.3 Comparing text and image platform

To better understand the amount and type of information extracted from image versus text platforms, we must explore the usage of the original platforms. In the case of text, Twitter has been categorized as a microblogging site, which fulfills a need for a faster mode of communication that lowers the user's requirement of time (Java et al., 2007). On the other hand, Instagram is a photo-sharing mobile application that allows users to take pictures and share them on the platform. The usage of photographs highlights the importance of visual self-presentation of the users (Marwick, 2015).

Some differences between the platforms rely on the users' intentions/motives. In the case of Twitter, Java et al. (2007) found that the main user intentions are: daily chatter, conversations, sharing information, and reporting news. Twitter users usually share short messages, links, videos, and some hashtags in their tweets; however, words and images are the main tools to share information, activities, and experiences (García-León, 2019). So, in general, sharing information and social interaction are the main intentions of using Twitter.

In the case of Instagram (image platform), Sheldon and Bryant (2016) found four motives for using the platform: surveillance/knowledge about others, documentation, coolness, and creativity. Also, in 2015, Lee et al. found that Instagram users have five primary social and psychological motives: social interaction, archiving, self-expression, escapism, and peeking (Lee et al., 2015), while Baker and Walsh (2018) concluded that Instagram has become popular for self-presentation and public display. According to the previous research, social interaction, identity construction, and self-promotion are strong factors for using Instagram.

Although social interaction motive is similar for using Twitter and Instagram, the differences (sharing information for Twitter, and identity construction and self-promotion for Instagram) could explain that with images we accessed to a higher amount of information than texts regarding beer-food pairing and context of consumption, since pictures could reflect consumers lifestyles where capturing and sharing pictures plays a core role.

Photography in consumer behavior could be an important source of information for gastronomy field, from which researchers could access to users' daily activities and their food culture, such as Instagram users utilize pictures of all sorts of things to present their personalities, lifestyles, and tastes. (Lee et al., 2015). Analogously, the higher amount of available food images from social media is a consequence of the taking pictures behavior, which has been widely spread among consumers, and it is reflected by the user's obsession to take pictures before eating foods and meals. This behavior could allow researchers to explore the context of consumption of the users and their preferred food and beverage pairings by avoiding laboratory settings.

In general, this research could have significant implications for food and beverage researchers, sommeliers, and chefs who try to understand food pairing, as this is the base of food product development (Galmarini, 2020). In this study, although certain food and meal combinations may have been identified due to tradition or culturally influenced, some food-food or food-beverage combinations could be used to improve or develop new successful pairings.

In this research, images and texts were useful to explore food-food and food-beverage combinations. Social media analysis revealed that text users shared concise and specific information but were also less informative, while image information resulted more complete regarding a specific topic, such as beer-food pairing. Our results propose that images could be a good source of information when researchers investigate the gastronomic context of consumption. In general, any social media platform which involves images could act as a good source of information when studying food and meal pairing, as this research suggests that for consumers is easier to share experiences through photographs than using texts in social media.

5. Conclusions

This study has great potential for informing food researchers about the importance of social media as a tool for understanding food and meal pairing and consumer behavior, particularly regarding the context of consumption in the gastronomic field. In general, images resulted in a more informative source than text; also, texts mainly shared individual consumptions, while images shared more social moments. However, more research should be done to improve the efficiency of the data analysis, to facilitate and shorten the time invested in analyzing image by image. Integrating other disciplines specialized in images, such as arts, design, and semiotics, could improve the way we use images for consumer research. Additionally, the use and analysis of images bring a new range of possibilities to better understand not only food pairing but food choice and consumption.

Some limitations of this research are that images from the Twitter platform were not analyzed, only those from Instagram, to separate Twitter as a text (primary) based platform vs. Instagram as an image (primary) based platform. Special attention must be taken in the content analysis when exploring consumption behavior due that the displayed food and meals could not be frequently consumed by the users but only on special occasions.

Acknowledgments

Authors wish to thank CONACYT-MEXICO for the scholarship (2017-2020 period) granted to Araceli Arellano Covarrubias for her PhD at the Biotechnology Postgraduate Program at the Universidad Autónoma Metropolitana (520074/574751).

The author P. Varela would like to thank funding to the Norwegian Fund for Research Fees for Agricultural Products (FFL) through the project “FoodForFuture” (project number 314318).

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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