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Gaining a deeper understanding of nutrition using social networks and user-generated content

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A B S T R A C T

Using user-generated content (UGC) on Twitter, the present study identifies the main themes that revolve around the concept of healthy diet and determine user feelings about various foods. Using a dataset of tweets with the hashtag "#Diet" or "#FoodDiet" (n = 10.591), we first use a Latent Dirichlet Allocation (LDA) model to identify the food categories most discussed on Twitter. Then, based on the results of the LDA model, we apply sentiment analysis to divide the identified tweets into three groups (negative, positive and neutral) based on the feelings expressed in corresponding tweets. Finally, the text mining approach is performed to identify foods according to the feelings expressed about those in corresponding tweets, as well as to derive key indicators that collectively present the UGC-based knowledge of healthy eating. The results of the present study show that among the foods most negatively perceived in the UGC are bacon, sugar, processed foods, red meat, and snacks. By contrast, water, apples, salads, broccoli and spinach are evaluated more positively. Furthermore, our findings suggest that the collective UGC knowledge is lacking on such healthy foods as fish, poultry, dry beans, nuts, as well as yogurt and cheese. The results of the present study can help the World Health Organization (WHO), as well as other institutions concerned with the study of healthy eating, to improve their communication policies on healthy products and preparation of balanced diets.

1. Introduction

Noncommunicable diseases (NCDs), also known as chronic diseases, are the result of a combination of genetic, physiological, environmental and behavioral factors. The factors that lead to NCDs include unhealthy diet, physical inactivity, smoking, and alcohol consumption (Dubé et al., 2014; Collins et al., 2019). NCDs are of a particular concern in low and middle-income countries, since the population's diet in these countries is characterized by nutritional deficiencies (Thomas and Quinn, 2008; Popkin, 2014). Interestingly, although NCDs are predominant in countries with medium or low income, obesity and the negative health consequences caused by NCDs are more pronounced in countries of medium and high-income levels (Popkin, 2014).

Previous research on NCDs has sought to understand their causes and to find solutions to avoid their consequences for the society. One of the leading causes NCDs is an unhealthy diet (Dubé et al., 2014; Akselrod et al., 2019). Therefore, a healthy diet is an important factor that contributes to individual health (Cade et al., 1999). In the present study, we take the World Health Organization's (WHO) (WHO reports, 2018) recommendations about a healthy diet as a starting point. Specifically, the WHO prescribes "eating more fruit, vegetables, legumes, nuts and grains; cutting down on salt, sugar and fats. It is also advisable to choose unsaturated fats, instead of saturated fats and towards the elimination of trans-fatty acids. An unhealthy diet is one of the major risk factors for a range of chronic diseases, including cardiovascular diseases, cancer, diabetes and other conditions linked to obesity" (see WHO reports, 2018).

It should be noted that, after the International Nutrition Conference of the WHO in 1992, governments, civil society, and companies have taken measures to promote consumers' awareness of the importance of adequate nutrition. These initiatives have been part of what is known as nutrition education of the population, i.e. a combination of different strategies intended to help consumers to develop appropriate attitudes, skills and motivations regarding healthier food and nutrition (Contento, 2011).

The major goal of nutritional education is not only to provide consumers with nutritional information, but also to accompany them in all aspects of daily life so that help them to modify their eating behavior towards a healthier and more nutritious diet. However, despite recommendations from the WHO and the efforts made by governments, civil society, and businesses, unhealthy living habits and unhealthy eating have considerably increased since 1992, such as a sedentary lifestyle, alcohol consumption, or eating saturated fats and high amount of sugar or red meat (Mazzocchi et al., 2009).

In addition, the daily life of people in the developed countries is characterized by unhealthy eating patterns such as skipping meals, eating out of the home, or eating snacks (Wahlen et al., 2016). Therefore, in order to effectively promote healthy eating, organizations

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should be provided with relevant information about cultural and individual factors that lead to an unhealthy diet (Bonke, 1996). Moreover, research on individual nutrition behavior can be intrusive and costly (de Castro, 1991), so it can be difficult to obtain sufficient data on individuals who follow an unhealthy diet (Zhou and Zhang, 2017; Samuels et al., 2017) in order to study their habits in the search for improvements related to healthy diets and healthy lives. Consequently, a healthy diet should provide the necessary nutrients to the body and thus is the key to good health and prevention of NCDs (Akselrod et al., 2019).

Therefore, there is evidence that leading a healthy balanced diet can reduce mortality and the risk of contracting illness, including coronary heart disease and cancer, among others (Cade et al., 1999). Other authors also stated that eating a healthy diet reduces the likelihood of becoming overweight or chronically ill (Adriaanse et al., 2011). Consequently, a healthy diet requires actions such as increasing the intake of fruits and vegetables and reducing the amount of salt, saturated fat, and sugar, among other recommendations (Macdiarmid, 2012). These benefits have incited users' interest in a healthy diet and its tendency to growth of interest as can be seen in the queries searched in the most used search engine in the world, Google (see Fig. 1). The number of searches of the term “healthy diet” has steadily increased since 2014. In Fig. 1, the Y axis shows the value of interest in the searches made by users of this search engine (maximum = 100, minimum = 0) (Reyes-Menendez et al., 2018a), while the X axis shows the period of years analyzed using Google Trends, as this software started to collect data from 2014 to the present.

Therefore, as can be seen in Fig. 1, the interest in healthy eating has considerably increased in the last 5 years. The same tendency has been reported by Choi and Varian (2012) or Önder and Gunter (2016).

In this regard, the WHO proposed in 2018 using digital platforms to promote and communicate healthy habits both individually and collectively for countries. These digital platforms would also contribute to prevention and treatment of NCDs by helping people to better understand the consequences of unhealthy eating.

A feasible option, in this context, is using online social networks as an alternative to exploratory, intrusive, and high-cost studies (de Castro, 1991). In social networks, users document their daily activities, including the choices they make about what they eat (Abbar et al., 2015). Social networks are platforms where users exchange their opinions in a natural way with other users (Reyes-Menendez et al., 2019). In recent years, social networks have changed the way users generate and obtain information. This is particularly true of social networks such as Facebook and Twitter where content about users' everyday activities is shared systematically on a daily basis (Odea et al., 2018).

Previously, content producers were in charge of producing information, while the media determined which information was to be shared. Social networks have changed the way in which information is produced and consumed (Saura et al., 2018). At present, information is decentralized, and it is the users themselves who decide which individual users they want to follow. This has led to a transformation of individual users from mere receivers of information to creators of content (Bennett et al., 2017).

Furthermore, owing to the algorithms of detecting which content users have previously seen, users can discover other users with whom they have affinity through relevant personalized suggestions from social networks. Suggested content, which is highly personalized, can influence the behavior and decision making of other users (Reyes-Menendez et al., 2018b).

Therefore, the starting point of the present study is the assumption that the content generated by users in social networks known as User-Generated Content (UGC) can influence other users' decisions about food and healthy diet (Abbar et al., 2015; Odea et al., 2018). Therefore, an analysis of how the concept of healthy diet is represented in social networks can both promote healthy eating and disseminate information about the importance of healthy nutrition and good health by government agencies, institutions, and policy makers.

Consequently, the aim of the present study is to identify the main topics and their sentiments (positive, negative and neutral) that provide meaning to the concept of healthy diet in the UGC in Twitter for which a data mining and topic modeling process was developed (Odea et al., 2015). Of note, the present study is exploratory, rather than hypothesis-testing, as our major goal is knowledge discovery (Corbin and Strauss, 2008). This methodological orientation brings originality to the present study. A major contribution is that our results provide meaningful implications for public agents and policy makers in the area of food education in social networks—an area which has been largely overlooked in previous (Ghosh and Guha, 2013; Närvänen et al., 2013; Kulshrestha, 2016; Jaeger et al., 2017).

The remainder of this paper is structured as follows. In Section 2, we review the literature on the concept of healthy diet, as well as the Food Guide Pyramid, and discuss previous studies on the UGC on Twitter. Next, in Section 3, we present the methodology used in the study to identify the main topics in user content related to the concept of healthy diet. Results are presented in Section 4. Conclusions are drawn in Section 5.

2. Literature review

The rapid growth of the number of users who create profiles in social networks and the extensive use of different social platforms to generate content around different topics resulted in social networks has

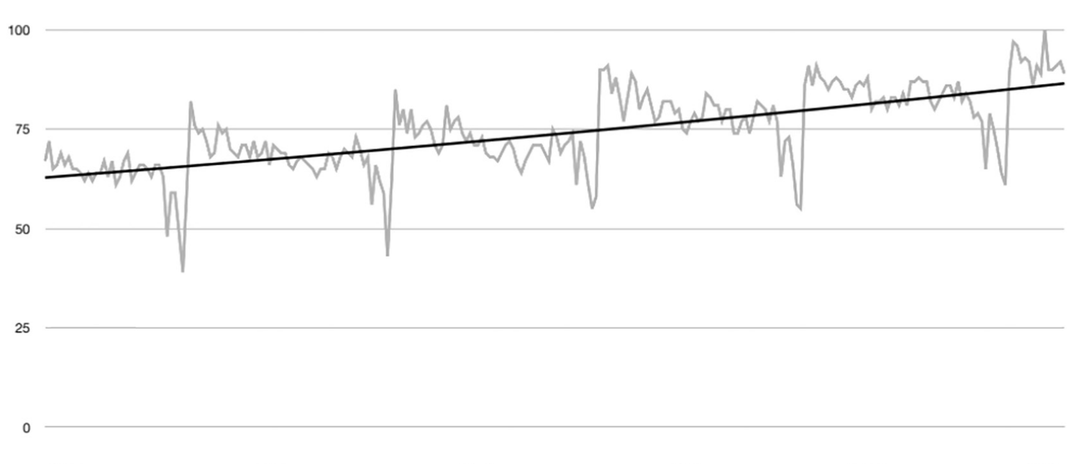

Fig. 1. Search trends on “healthy diet” in Google Trends report (2014–2019).

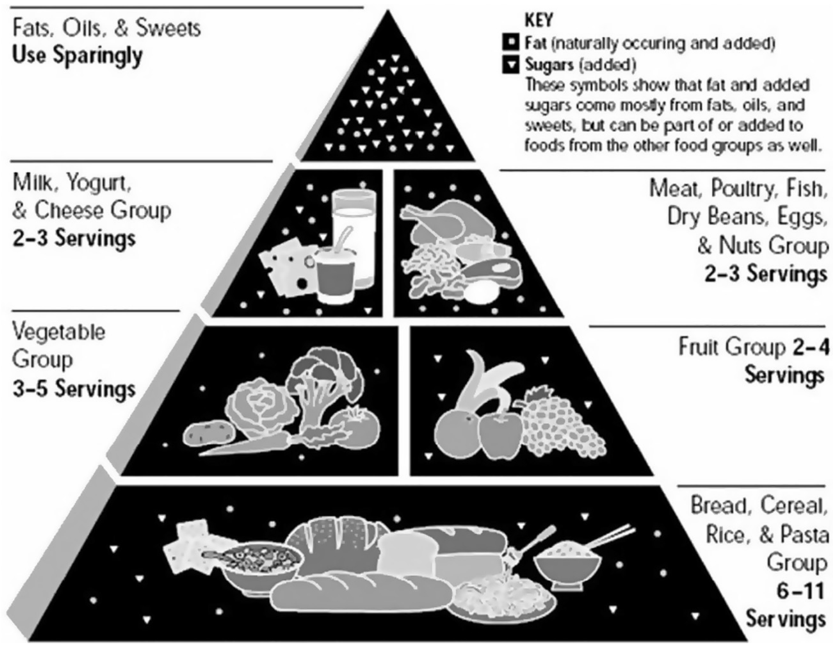

Fig. 2. Food pyramid published by USDA in 1992.

become a major source of data (Kulshrestha et al., 2015; Abbar et al., 2015; Chung et al., 2017).

One of the main advantages of social networks as a source of data on consumer behavior is that the information generated by users on social platforms already has a network structure; accordingly, users can be investigated as a whole rather than in isolation (Hubert et al., 2017; Saura and Bennett, 2019).

This general characteristic of social platforms, along with the exuberance of data generated on specifically the Twitter platform, has made Twitter a valuable source to collect the data on public health (Prasetyo et al., 2015), the environment (Reyes-Menendez et al., 2018a), obesity (Paul and Dredze, 2011), or a healthy diet (Culotta, 2014).

In addition, Twitter has been widely used to perform awareness campaigns on eating habits (Prier et al., 2011). Typically, such campaigns have a clear purpose and are structured around a concept easily understood by users (Hubert and Kenning, 2009). Some examples of visual campaigns and simple reminders include the Healthy Eating Plate developed by Harvard Medical School and Harvard T.H. Chan School of Public Health and the My Plate campaign created by the US Department of Agriculture (USDA) to help users remember what foods should be included in their diet daily, and to make good nutritional choices (see Section 2.1). Another example of a campaign developed by nutritional organizations is the campaign for cancer awareness by the WHO in 2004, which aims to increase the daily intake of fruits and vegetables, since this eating behavior reduces the risks of NCDs, known as "Cancer Control, Knowledge into Action". This worldwide campaign has been held in different countries and is represented by different institutions such as Cancer Society of New Zealand, US National Cancer Institute, or the Ministry of Health of Chile (Zacarias et al., 2006), among many others. Finally, another easily recognizable visual campaign worldwide is the Food Guide Pyramid developed in 1992. This pyramid visually represents the foods that should make up the basics of a healthy diet in the base and the foods that should have only a sporadic consumption at the top for the first time.

2.1. The food guide pyramid

Over a century ago, based on the nutritional recommendations about the main food guides, the USDA introduced initiatives that aim to improve citizens' health and to prevent NCDs through the development of Food Guides. The importance of nutritional indications can hardly be overestimated, as people need to eat daily; however, in most cases, food consumption is driven not that much by a physiological need, but by cultural factors (Carvalho, 2006; Culotta, 2014).

From 1916 to 1930, the USDA has developed initiatives such as "Good for Young Children" and "How to Select Food" in order to establish a starting point on food groups and household measures, with the focus on protective foods. Later, in 1940, the USDA created "A Guide to Good Eating (Basic Seven)" that established the foundation diet that accounted for nutrients' adequacy. From 1956 to 1970, the USDA promoted the "Food for Fitness, A Daily Food Guide (Basic Four)" that laid down the foundation of diet approach. In 1979, USDA introduced the "Hassle-Free Daily Food Guide", which was later developed into "Dietary Goals for the United States". In 1984, the USDA presented the "Food Wheel: A Pattern for Daily Food Choices" first illustrated for a Red Cross nutrition course as a food wheel.

However, many people still remember the Food Pyramids (the Food Guide Pyramid and MyPyramid), the USDA's food guidance symbols before the current MyPlate. The first Food Guide Pyramid was introduced in 1992 and focused on a total diet approach developed to raise awareness about new food patterns. Food Guide Pyramid focused on the concepts of variety, moderation, and proportion. This USDA initiative was very well received around the world and, as a consequence, many food guidance systems worldwide were based on the original Food Guide Pyramid developed by the USDA in 1992. In 2015, the USD introduced "MyPyramid Food Guidance System" to update the initial Food Guide Pyramid. However, it is important to highlight that food pyramid is no longer in use, as it was replaced by the "MyPlate" in 2011.

The Food Guide Pyramid was taken as the base of many food guidance systems around the world, and its goal was to improve nutrition and nutritional sustainability worldwide (Jones et al., 2018), Fig. 2 shows the Food Guide Pyramid designed by the USDA in 1992 (Jones et al., 2018). In the original food pyramid, at the bottom of the pyramid are bread, cereals, rice and pasta, since it is necessary to take between 6 and 11 servings of these foods weekly. Each of the food groups has different recommended amounts. As can be seen in Fig. 2, these quantities become smaller in the upper levels of the Food Pyramid.

Table 1
Main previous studies on UGC and healthy diet.

Authors	Description
Abbar et al. (2015)	This study develops a model to predict obesity and diabetes using Twitter (as the main source of data) combined with demographic and psychographic data. For this end, a database downloaded from the social network and information from the censuses are used
Kulshrestha et al. (2015)	This study uses Twitter's UGC to identify the topics related to the so-called 'Information Diet'. It also compares the diet presented in traditional media with the one presented in social networks.
Chung et al. (2017)	This study uses the Twitter platform and a connected device such as Fitbit to improve the health, physical activity, and diet of the participants. The results show that, owing to UGC on Twitter and gamification present in the physical activity device, three variables measured in the study (physical activity, health, and diet) have improved.
Culotta (2014)	This study compares the data obtained from Twitter with the data obtained using traditional methodologies. The results show that, in 20 of 27 analyzed topics, the predictive capacity of the research carried out on Twitter improves the predictive capacity of traditional methodologies.
Eijl (2016)	This study analyzes the influence of Twitter content creators on the topics of cancer and food.

2.2. User generated content analysis

UGC is a type of content generated by users on the Internet. Typically, UGC comes from digital platforms or social networks. In this type of content, users express their opinions and comments on specific topics. UGC is usually composed of reviews, comments, opinions, interactions between the user and the brand, and so forth. Various methodologies have been applied to analyze this type of content, including data-mining approaches, application of models such as LDA, textual analysis, sentiment analysis (SA), and other mining opinion techniques (Stieglitz et al., 2018). In the present study, we analyze the UGC related to food and healthy eating in Twitter. Several studies have emphasized the cultural, rather than physiological, dimensions of eating habits in different countries (e.g., Abbar et al., 2015). These situations frequently result in that the amount of calories consumption exceeds people's physiological need and, as a result, a part of the population becomes overweight and develops unhealthy habits (Nasser, 1988; Orji and Mandryk, 2014).

Several previous studies have addressed the issue of food and dieting using UGC (see Table 1 for a summary). For instance, Abbar et al. (2015) developed a model to predict obesity and diabetes based on information from Twitter. To refer to the UGC on the diet generated by Twitter users, Kulshrestha et al. (2015) developed the concept of Information Diet (ID). Along similar lines, Chung et al. (2017) used Twitter to generate content related to physical activity, healthy habits, and healthy diet in combination with the use of Fitbit devices. The results of this study showed that users improved their physical activity and that their diet became healthier. In another study, Culotta (2014) demonstrated that, in 20 of 27 analyzed topics, the predictive capacity of the research carried out on Twitter improved the predictive capacity of traditional methodologies.

In terms of methodology, the present study follows Saura and Bennett's (2019) research. Also, our focus on social interactions and the analysis of frequency of different topics in the tweets are also informed by Miller et al. (2017) and Liu et al. (2017).

3. Research questions

As mentioned before, traditional methodologies used to investigate user behavior regarding eating habits and diet are frequently expensive and intrusive (Abbar et al., 2015; Zhou and Zhang, 2017; Samuels et al., 2017). In this respect, social platforms offer new opportunities for an in-depth investigation of consumer behavior (Ghosh and Guha, 2013). To this end, UGC has frequently been used as data source (Kulshrestha et al., 2015; Chung et al., 2017) to better understand different aspects related to healthy eating (Culotta, 2014). The first research question addressed in the present study is as follows:

RQ1: Can we identify user diet preferences through the analysis of UGC on Twitter?

Leading an active life based on a balanced diet helps develop healthy habits that improve long-term health (Verplanken and Faes, 1999). The nutritional pyramid created by the USDA contains relevant recommendations healthy eating patterns. However, individual diets are influenced by both cultural aspects and by the information that users receive on a daily basis (Eijl, 2016; Abbar et al., 2015). The UGC on Twitter is among important sources of information that people receive about healthy eating. In this context, the second research question that we address is as follows:

RQ2: Are the foods, or groups of foods derived from the analysis of UGC on Twitter, the same as the standards of the food pyramid promoted by the USDA?

The content of Twitter posts is usually organized around themes, or topics. These topics can also be called categories. Previous research has demonstrated that such categories are usually associated with specific feelings, such as positive, negative, and neutral (Saura et al., 2019a) in health information (Scanfeld et al., 2010). In the context of the present study, the following question emerges:

RQ3: Are the foods topics identified in UGC on Twitter associated with different feelings?

As mentioned above, new research methodologies based on analyzing UGC in social networks offer new opportunities for both researchers and for those responsible for the development of health policies (Stieglitz et al., 2018; Närvänen et al., 2013). Also, compared to traditional methods, new methodologies based on the analysis of UGC in social media are less intrusive and cost-effective (Abbar et al., 2015; Culotta, 2014), and allow for larger amounts of data to be analyzed more quickly (Reyes-Menendez et al., 2018a, 2018b; Saura et al., 2019b). In this relation, the fourth question addressed is as follows:

RQ4: Is it possible to create a healthy diet by grouping the topics and foods with a positive feeling of the UGC on Twitter?

4. Research methodology

The methodology used in this study consists of three consecutive stages (see Saura and Bennett, 2019 for further detail). The first stage is the development of an LDA model that works in Python and identifies the themes in a database—in our case, a collection of tweets with the hashtag #Diet and #FoodDiet. Our sample consisted of a total of 10,591 tweets. In the second stage, SA was performed with a Support Vector Machine (SVM) type algorithm. Then, SA was used to identify which feelings the topics identified by the LDA are associated with. Finally, a text data mining process with the NVivo software was performed on these results. This last approach allowed us to identify, based on positive feelings expressed in tweets, the foods that make up a healthy diet.

4.1. Data sampling

In the first phase of tweet collection, Python software 3.7.0 was used to collect the tweets after connecting to the public Twitter API. The initial sample consisted of $n = 14{,}731$ tweets. The collected tweets were in English and contained the keyword "#Diet" and "#FoodDiet" in the tweet hashtag (Palomino et al., 2016; Reyes-Menendez et al., 2018a). After cleaning (which included eliminating repeated tweets, retweets, and tweets shorter than 80 characters), the final sample was reduced to a total of $n = 10{,}591$ tweets. The period of data collection was April 9–23, 2019.

The tags "#Diet" and "#FoodDiet" in Twitter were selected following several previous studies, such as Vidal et al. (2015), Vidal et al. (2016), and Jaeger et al. (2017). These studies on healthy habits, types of meals consumed, and food preferences applied SA and data mining techniques to analyze Twitter-based content. In this research, we followed these studies in our tweets collection process to be able to draw conclusions related to a specific topic within the food sector and, in particular, health care (Kulshrestha, 2016).

4.2. Topic identification using LDA

The LDA model used in this research is based on a mathematical and probabilistic assumption that content is generated in two steps (Jia, 2018). The first step is to identify keywords within a content or database, where each word is encrypted in an independent document. In the second step, the distribution of the topics in a sample is randomly identified, and the main themes in the sample are found (Jia, 2018; Saura and Bennett, 2019) (see Eq. (1)).

$$\rho(\beta_{1:k}, \theta_{1:D}, Z_{1:D}, \omega_{1:D}) = \prod_{i=1}^{K} \rho(\beta_i)(\beta_1) \times \prod_{d=1}^{D} \rho(\theta_d) \times \sum_{n=1}^{N} \rho(Z_{d,n} | \theta_d) \rho(W_{d,n} | \beta 1_{:K,}{}^{Z}{}_{d,n}) \tag{1}$$

βi	distribution of word in topic i, altogether K topics
θd	proportions of topics in document d, in all D documents
z_d	topic assignment in document d
$z_{d,n}$	topic assignment for the nth word in document d, in all N words
w_d	observed words for document d
$w_{d,n}$	the nth word for document d

Consequently, the identification of the topics and words is set posteriori with the following approach (see Eq. (2)) using Gibbs sampling (Jia, 2018). In this study, the estimation was performed using Python software LDA 1.0.5.

$$\rho(\beta_{1:k}, \theta_{1:D}, Z_{1:D} | \omega_{1:D}) = \frac{\rho(\beta_{1:K}, \theta_{1:D}, z_{1:D}\omega_{1:D})}{p(w1: D)} \tag{2}$$

4.3. Sentiment analysis development

After identifying the issues related to healthy eating, we applied an algorithm developed in Python that works with machine learning. In this case, this process requires the training of an algorithm with text data mining to subdivide the sample into segments expressing positive, negative and neutral sentiments with respect to each sentiment identified. This procedure resulted in identification of 379 samples trained related to healthy eating and diet. Then, SA was applied to each topic identified following the process presented in Fig. 3.

The effectiveness of the SA process is measured with the Krippendorff's alpha value (KAV), which is a measure of effectiveness of the algorithm that works with machine learning. According to Krippendorff (2004a), when $\alpha \geq 0.800$, the reliability of the results and conclusions is high. In order to draw conclusions based on tentative statements, a minimum of $\alpha \geq 0.667$ must be obtained; if a value of $\alpha < 0.667$ is obtained, the conclusions will have a low reliability (Krippendorff, 2004b).

4.4. Textual analysis process

The next step was to perform textual analysis with text data mining techniques on the identified healthy eating topics. For this purpose, we used NVivo at different stages in which the tweets were categorized into the following three nodes: Positive (N_1), Neutral (N_2), and Negative (N_3). Here, nodes are predefined data containers grouped according to their characteristics. The design and development of nodes and their contents is used to make the results have the highest possible descriptive and exploratory quality.

In order to perform this process, we classified the sample according to (i) the frequency of repetition of the words that make up the dataset, (ii) the keywords' total weight in the dataset attending the weighted percentage (WP), and (iii) filtering those words that do not add significance value to the research objective (Newton-John, 2018). These criteria were followed to group the tweets according to the sentiments expressed in them into the three different nodes (positive, negative, and neutral) (Krippendorff, 2004a; Zamawe, 2015). In the next step, Saura and Bennett's (2019) method was applied to these three datasets to extract insights.

In this type of approximations, the WP is taken into account. WP represents the weight of the indicators grouped into nodes according to the times they are repeated, thus being the weight of the nodes in terms of the total data in the database (Krippendorff, 2013; Newton-John, 2018).

5. Results

The results of the LDA process yielded a total of 11 food-related topics (see Table 4). The LDA process automatically categorized keywords related to the topics. Based on those keywords, topics were named (see also Jia, 2018). A rule of thumb regarding topic naming is to consider 10–20 most repeated words and try to form a phrase with those words that would make sense. The descriptions of the topics were developed using the words that make up the topic based on the content of the topics. This step is a standardized process in the LDA models (Büschken and Allenby, 2016; Miller et al., 2017). Of note, subtopics within the previously identified topics were also found (see Tables 2 and 3).

After the classification of the topics, we ensured that the results aligned well with recommended Krippendorff's alpha value thresholds (KAV) (see Table 4).

In the next step, we identified the feelings associated with the topics and established the key indicators of each topic. To this end, using NVivo, we established three nodes (N_1 = positive, N_2 = negative, and N_3 = neutral). Tables 5–7 summarize the topics divided into nodes, the key indicators or insights found in the collected sample, and the number of pieces of text where each of the topics appeared in the dataset.

Therefore, identification of key indicators or insights is an exploratory process of analyzing and identifying the content of each individual node based on the WP and the contents of each topic (Krippendorff, 2013).

6. Discussion

Digital channels and social networks have been widely used in previous research to investigate public health and healthy dietary habits (Ghosh and Guha, 2013; Närvänen et al., 2013; Kulshrestha, 2016; Odea et al., 2018). Based on the analysis of the UGC of Twitter users on a specific topic (e.g., Saura and Bennett, 2019), the results of the present study demonstrate that it is possible to evaluate Twitter users' food sentiments (see also Zhou and Zhang, 2017).

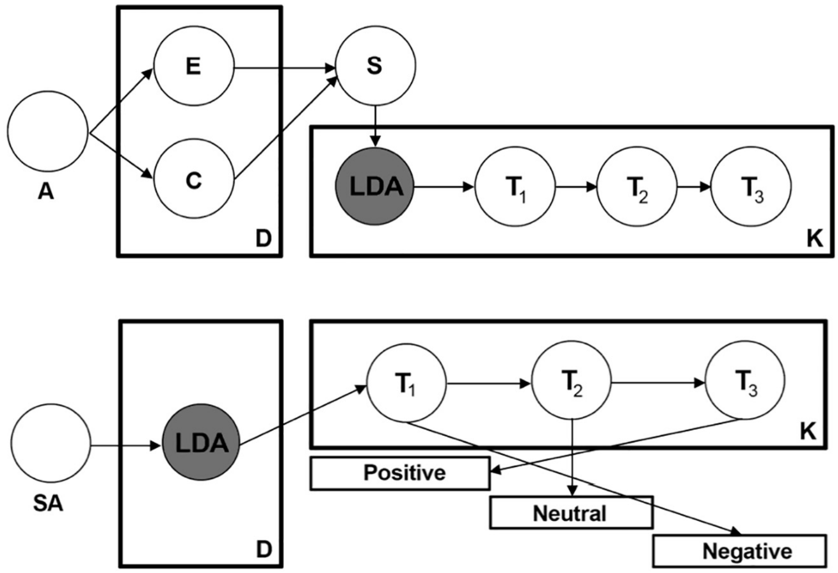

Fig. 3. Process of Sentiment Analysis and LDA classification developed by Saura and Bennett (2019).

Our results demonstrate that users have generally positive feelings towards healthy diet and share their experiences of healthy eating habits in social networks. Reyes-Menendez et al. (2018a, 2018b) concluded that the UGC and its feelings may be an indicator of public opinion and, therefore, may affect public health (Ekenga et al., 2018).

Considering that positive feelings about healthy food were identified primarily about foods such as fruit and vegetables, we can extrapolate this positive evaluation to user perceptions of these foods. This UGC-based insight can be used to improve food awareness campaigns that fight against NCDs such as obesity (see Ghosh and Guha, 2013).

While our results show that users positively perceive foods such as apples, salad, bananas, broccoli, or spinach, there is also a gap in how these users understand that they should complete their diets by adding new foods that may not be perceived as positively, but which are healthy if consumed in moderate amounts, such as coffee (Bae et al., 2014), potatoes (Haase, 2008) or eggs (Griffin, 2016).

Also, while there is scientific evidence that foods such as fish, poultry, dry beans, and nuts are good for public health according to WHO, our results show that Twitter users have doubts about health benefits of these products. Several previous studies (e.g., Herráez et al., 2017) demonstrated that social networks can be used to interact with users and establish lasting conversations over time between institutions and consumers. This strategy should be followed by institutions such as Food and Agriculture Organization (FAO), the WHO or the USAD to promote and recommend a healthy consumption of foods that, although healthy, can be perceived as unhealthy (e.g. our results showed that products such as chocolate, wine, milk, coffee, eggs, potatoes, and diets such as vegan and ketogenic/protein were perceived as neutral).

Also, as demonstrated by Bergström and Jervelycke Belfrage (2018), digital channels and the UGC can be a way to disseminate information, make recommendations, and raise awareness among the population on a specific topic. In this connection, in line with Vydiswaran et al. (2018) and Khulbe and Pathak (2019), our findings show negative user evaluations of sugar and carbohydrates, industrial sweet products and carbohydrates, food, red meat, pizza, bacon and snacks. Therefore, policy makers, public institutions, and food companies should identify consumers' concerns regarding unhealthy foods and recommend good practices of healthy eating.

Public opinion expressed on social platforms like Twitter is linked to public health (Ekenga et al., 2018). Therefore, policy makers such as FAO, WHO and USDA should consider strengthening their strategic plans by incorporating their dietary recommendations in social networks—as, for instance, in the model proposed by Kulshrestha et al. (2015) known as ID in social media.

7. Conclusions

The present study focused on the UGC around the theme of healthy diet and how it differs from the food pyramid proposed by USDA. Based on our results, the following conclusions can be made with respect to the three research questions addressed.

First, concerning RQ1 the answer is affirmative. Our findings demonstrated that Twitter users feel positively about healthy food (mostly fruit and vegetables, e.g. apples, salad, bananas, broccoli and spinach).

Table 2
Identified topics related to diets in UGC.

Topic name	Topic description	WP	Sentiment
Diseases	Identification of diseases and dementias resulting from unhealthy eating.	4.49	Negative
Healthy food	Grouping healthy foods and providing examples of diets beneficial for health	4.32	Positive
Sugar	Discussion of sugar-containing foods (pastries and industrial products)	3.18	Negative
Fruit and vegetables	Discussion of fruit and vegetables as the basis of a healthy diet	3.13	Positive
Proteins	Comments and dietary recommendations related to proteins and their benefits for health	3.05	Neutral
Carbohydrates	Identification of health problems related to excess of carbohydrates in diet	2.93	Negative
Ketogenic	Advice and comments on ketogenic diet and a discussion of its impact on health	2.47	Neutral
Healthy habits	Discussion of healthy habits and health benefits of sports and active lifestyle	2.39	Positive
Processed Food	Discussion of processed foods and their damage to health.	2.13	Negative
Bodybuilding	Discussion of sports culture and healthy diet, and of their benefits for health.	2.09	Positive
Vegans	A social movement among vegans and vegetarians and the discussion of their eating habits	1.68	Neutral

Table 3
Identified sub-topics related to diets in UGC.

Topic name	Sub-topic description	WP	Sentiment
Fruits	Comments and diets based on fruit feeding	1.49	Positive
Vegetables	Vegetables and corresponding tips on vegetable diets	1.20	Positive
Meats	Consequences of meat eating on human body	1.06	Negative
Vinegar	Health benefits of vinegar in a balanced diet	0.79	Positive
Water	Role of water in a healthy diet	0.67	Positive
Eggs	Health benefits of different egg diets	0.59	Neutral
Apples	Importance of apples for health and a balanced diet	0.59	Positive
Coffee	Properties of coffee and its impact on the human body.	0.42	Neutral
Salads	Benefits of salad diets	0.41	Positive
Milk	Comments and opinions on health benefits of drinking milk	0.41	Neutral
Wine	Comments and opinions on health benefits of drinking wine	0.39	Neutral
Vitamins	Identification of vitamins and foods rich in vitamins	0.38	Positive
Bananas	Health benefits of eating bananas	0.33	Positive
Chocolate	Comments on chocolate and its impact on health	0.31	Neutral
Bacon	Comments on bacon and its impact on health	0.30	Negative
Pizza	Comments and opinions on pizza and its association with diets high on carbohydrates.	0.28	Negative
Broccoli	Healthy recipes containing broccoli	0.25	Positive
Potatoes	Comments and opinions on potatoes and their role in diets high on carbohydrates.	0.25	Neutral
Chicken	Comments and opinions on eating chicken and associated health benefits	0.22	Positive
Spinach	Discussion of health benefits of spinach	0.21	Positive
Snacks	Comments and opinions on eating processed foods and sedentary diets	0.21	Negative

Table 4
SA conclusions' reliability (Krippendorff's alpha).

Conclusions reliability	Krippendorff's alpha value	Sentiment	Average KAV
High	$\alpha \geq 0.800$	Positive	0.759
Tentative	$\alpha \geq 0.667$	Negative	0.798
Low	$\alpha < 0.667$	Neutral	0.691

Second, as to RQ2 we found that the foods that evoke most positive feelings in Twitter-based UGC do not fully match food pyramid promoted by the USDA. Specifically, in Twitter-based UGC, less attention was paid to fish, poultry, dry beans, and nuts. This suggests that there is a need to implement policies that would better inform the population about the health benefits of these products, because the total of food themes identified does not coincide with food priority standards promoted in the food pyramid of USDA and neither in the current MyPlate food guide.

With regard to RQ3, our results demonstrated that the most negative feelings were expressed in the topics on sugar and carbohydrates contained in pastries and industrial sweet products and carbohydrates (for causing obesity disorders), processed food, red meat (for its relation to heart problems), as well as other unhealthy foods, such as pizza, bacon and snacks.

In contrast, foods mentioned in tweets with positive connotations included fruits and vegetables, water, vinegar, apples, salads, vitamins, as well as chicken and spinach. Finally, as concerns RQ4 the answer is affirmative, since our methodology allowed us to group, according to topics and feelings, the analyzed food classifications, as well as to compose a food pyramid and analyze which foods do not appear in UGC-based priorities. However, as discussed above, the perceptions of healthy foods in Twitter-based UGC do not fully agree with the recommendations made by the WHO.

Table 5
Results for N_1 for diet positive key indicators.

N_1	Key indicators	Count
Healthy food	Healthy foods are the basis of a balanced diet. Healthy foods are linked to eating movements and trends (e.g., vegans or vegetarians).	682
Fruit and vegetables	Fruit and vegetables are essential for a healthy diet and include vitamins B, C, A, E and K.	621
Healthy habits	Sport, healthy food, and social time with the family are the backbone of healthy habits.	371
Bodybuilding	Body culture and sports activities (e.g. gym and jogging) are linked to the movement of bodybuilding and a healthy diet.	214
Fruits	Fruits are a fundamental part of a healthy diet. Containing water and fiber, fruits help to maintain healthy habits.	340
Vegetables	Vegetables help prevent diseases. Vegetables are the basis of a healthy diet, although their consumption can be counterproductive if consumed in excess.	291
Vinegar	Vinegar consumption helps to prevent diseases. Vinegar helps to accelerate the metabolism.	124
Water	Water is the basis of liquid food and is necessary to maintain a healthy diet. It is linked to sports and healthy habits.	204
Apples	It is a food for lovers of healthy habits. Apple consumption is linked to vegan eating style.	145
Salads	Salads are a source of vitamins A and C. Salad consumption is linked to healthy eating movements (e.g., vegans and vegetarians)	203
Vitamins	Vitamins are essential to healthy eating.	271
Bananas	Bananas are beneficial for the heart and skin. Consumption of bananas is linked to sports activities.	129
Broccoli	Broccoli is a source of fiber that helps the proper functioning of the human body.	121
Chicken	Chicken meat is a source of protein that helps maintain a healthy diet. Eating chicken meat is linked to gym and intensive sports activities.	101
Spinach	Spinach is a source of magnesium and vitamins A and C.	94

Table 6
Results for N_2 for diet negative key indicators.

N_1	Key indicators	Count
Diseases	Diseases are a result of unhealthy eating based on red meat and foods such as bacon, milk, snacks, or food in general.	310
Sugar	Excessive sugar consumption is linked to obesity and heart-related diseases.	291
	Saturated sugars are linked to snacks and sweet foods and causes diseases such as pancreatic cancer or high blood pressure.	
Carbohydrates	Carbohydrates are related to diseases such as depression, diabetes, and blood pressure issues.	104
	Diets based on carbohydrates are linked to obesity and weight gain that causes mobility problems.	
Processed Food	Diets based on processed foods are linked to heart problems, as well as cancer or obesity.	301
Meats	Meat eating can be unhealthy if consumed in excess.	205
Bacon	Eating bacon is linked to digestive diseases and cancer.	190
	Bacon has the highest negative impact in UGC.	
Pizza	Pizza contains large amounts of carbohydrates and can cause heart problems and obesity.	97
Snacks	Snacks are sources of saturated oils and fats.	139
	Snacks are linked to fried foods and fat.	

Table 7
Results for N_3 for diet neutral key indicators.

N_1	Key indicators	Count
Proteinas	Proteins are a key component for tissue repair.	94
	Proteins should be consumed after sports activities.	
Ketogenic	Ketogenic diet leads to fast fat burning	112
Vegans	The vegan movement is based on organic and green foods.	131
Eggs	Eggs are among the best foods for protein intake.	89
	When consumed in excess, eggs can cause diseases related to obesity and poisoning.	
Coffee	Coffee burns fats and helps improve physical and mental performance.	120
Milk	Milk is rich in proteins and carbohydrates and is linked to a balanced diet and sports.	77
Wine	Wine improves eyesight and helps prevent stress. It can also help improve dental and heart health.	64
Chocolate	It is a source of antioxidants and lowers blood pressure.	92
	Excessive consumption of chocolate causes diseases such as obesity.	
Potatoes	Potatoes are a source of carbohydrates and, in reasonable amounts, can help maintain a healthy diet.	78

7.1. Social and managerial implications

Taken together, the results of the present study underscore the need to investigate healthy eating habits using digital channels and social platforms. Our findings also provide meaningful practical implications for organizations and institutions such as FAO, WHO, or the USDA that are in charge of promotion of healthy eating. Specifically, our results may help improve their health communications and public health education policies. In addition, based on our findings, practitioners in the food health sector can establish communication policies and practices to improve public information about healthy foods, as well as the relation of unhealthy foods with diseases.

In addition, our results can help improve the decision making of food company executives and institutions food education institutions. Our findings can also be used contribute to the improvement of nutrition education, as the results of our analysis demonstrate the current knowledge in the society about healthy eating and suggest areas that should be educationally reinforced in terms of healthy diet.

With regard to social implications, in food education incentives using digital channels, institutions such as FAO, WHO or USDA should also consider how users behave in these environments and how they interpret messages on topics such as #HealthyDiet or #FoodDiet, which will undoubtedly benefit public health knowledge in the medium and long term.

7.2. Theoretical implications

As concerns theoretical implications, other researchers can use our results to improve their studies in the field of public opinion and public education on food and health, as well as to investigate the trends in specific diets that may pose a long-term health risk. Moreover, the results could be used to generate quantitative studies or models that measure the relationships established between the identified topics. For example, if researchers take these insights as variables and constructs for their models, they may be able to enhance their understanding of whether there are positive links between them by developing, for instance, models based on Partial Least Squares Structural Equation Modeling (PLS-SEM) or SPSS, Analysis of Moment Structures (AMOS) among others, thus contributing to the field of research that emerges from approaches that extract knowledge from large amounts of data based on UGC.

Also, academics can use our results to better understand the healthy diet sector on social media and to focus on the development of research within this field. In addition, they can focus on content analysis by users of different social networks to better understand user healthy eating habits.

One of the limitations of the present study is a relatively small sample size. Therefore, further investigations using larger-scale datasets are recommended. In future research, it would also be necessary to conduct longitudinal studies to trace the evolution of healthy education and to timely identify riskier tendencies in healthy eating. Finally, the present study is exploratory and based on UGC, rather than on clinical evidence. In further research, a more comprehensive picture of eating habits and healthy food perceptions could be obtained if UGC analysis is complemented by questionnaires or in-depth interviews.

Declaration of competing interest

The authors of this paper declare that there are not any conflict of interest.

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