Research article

Marketing challenges in the #MeToo era: gaining business insights using an exploratory sentiment analysis

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ABSTRACT

The #MeToo movement is among the most impressive social movements of recent years that have attracted stakeholders' attention and changed social mindsets. The present study seeks to provide a deeper understanding of the challenges involved in the #MeToo movement by identifying the main issues regarding business and marketing activities. To this end, the analysis of user-generated content (UGC) on Twitter was performed to extract the tweets with the hashtag "#MeToo" (31,305 tweets). Then, a Latent Dirichlet Allocation (LDA) model was applied to this database to identify topics. In the next step, using a Supervised Vector Machine (SVM) type analysis, we classified the tweets according to the sentiment they express (positive, negative, and neutral). Finally, we performed data text mining using the NVivo software. Our findings underscore the importance of (i) gender equality in communication campaigns, (ii) gender equality at work and (iii) social mobilizations in social networks, as well as suggest that (iv) marketing advertisers should become more inclusive and respectful in their advertising and marketing campaigns. The identified topics may be a starting point for future research on social movements, sociology, sexuality, or machismo in work environment, business and marketing strategies.

1. Introduction

In April 2019, in a *Guardian* article, different advertising female gurus gave their opinions about sexism in advertising and marketing (Fox, 2019). The author also discussed sexism in advertising and its relation to the #MeToo movement, a movement in social networks that gave visibility to sexism and sexual harassment (Fox, 2019).

Sexism, defined as a bias in treatment of people of different genders, has been the reality in many cultures throughout history (Hammond et al., 2018). Gender inequality is reflected in many aspects, such as access to resources or decision making (Mills, 2008). The main aim of sexist ideologies is to preserve gender inequalities in the society (Glick et al., 2000; Brandt, 2011). This leads to a critique of women in political or managerial positions (Connor et al., 2016) as compared to women in traditional roles (Hammond and Overall, 2016), thereby preventing women from pursuing their professional goals (Montañés et al., 2013).

According to Lakoff and Lakoff (2004), the words used to talk about a common reality give shape to a shared identity. Therefore, analyzing such keywords enables us to better understand the relations that underlie the societal structure. Several relevant studies have sought to investigate sexism and its terminology in different contexts. For instance,

Umera-Okeke (2012) focused on the analysis of sexism everyday discourse, while Pérez-Sabater (2015) and Bekalu (2006) analyzed how sexism is reflected in textbooks and newspapers, respectively.

Furthermore, there has been some research on the use of sexist language in advertising and marketing (e.g., Groza and Cuesta, 2011). More recently, some studies have addressed sexism in language content available on social platforms (e.g., Dubrofsky and Wood, 2014), such as Facebook (Strain et al., 2015; John et al., 2017; Drakett et al., 2018) or YouTube (Thelwall and Mas-Bleda, 2018).

These and many other studies have demonstrated that the main reason why sexist content has been used in the media is that, from the point of view of marketing and business, such content is more persuasive, attracts attention, and more easily generates a positive attitude towards the conveyed information (Brown and Stayman, 1992; Reichert et al., 2001). The effect of sexist content on consumers is more convincing and, therefore, is considered to be more effective (Aaker and Stayman, 1990; Wolin, 2003).

In recent years, many scholars have argued that it is necessary to study content on social platforms (John et al., 2018; Strain et al., 2015; Drakett et al., 2018). At present, many users access social platforms to tell others about their daily activities and experiences, as well as to share

their opinions (Dubrofsky and Wood, 2014). Importantly, if a story of a social platform user becomes viral, thus reaching a much larger audience than a specific group of followers, a social network movement is initiated (Reyes-Menendez et al., 2018a).

A main advantage of social platforms with respect to social movements is the fact that users are organized in networks of individuals with similar opinions and views (Palos-Sanchez et al., 2018). Among other social platforms, Twitter is an important network where users share their opinions. Discussions of various topics can happen around a profile, for example, @WomensEqualityUK, or around a hashtag (#), like #MeToo. This makes it possible to study the entirety of comments to such profiles or hashtags (Saura and Bennett, 2019).

Table 1 shows several main movements (and corresponding hashtags) that appeared on Twitter in recent years.

Previous research on tweets with specific hashtags (Sumiala et al., 2016) demonstrated the usefulness of the content published on social networks for studying terrorism, racism, gender equality, or sexual harassment. Figure 1 shows the growth of searches for different social movements related to gender equality and sexual harassment, such as #MeToo, #TimesUp, and #HeForShe.

As can be seen in Figure 1, among all the aforementioned movements, #MeToo has had the greatest reach. This movement against sexual harassment aptly reflects the reality that has been present, but that has not been sufficiently visible (Bhattacharyya, 2018; Kearl, 2018). Owing to social platforms, #MeToo has achieved visibility and coverage that united people all over the world around the #MeToo hashtag.

In part, the impact generated by the #MeToo movement can be explained by the statistics recently reported by the Gfk company (Kearl, 2018). According to the results of this report, 81% of women and 43% of men interviewed in the USA during 2018 had experienced some form of sexual harassment throughout their lives. First of all, 77% of the interviewed women confirmed having suffered from verbal sexual harassment. Furthermore, 51% of the women had been sexually touched without them willing or inviting such actions. Finally, 41% of women and 22% of men experienced cyber sexual harassment.

The #MeToo movement was launched in 2006 by Tarana Burke to support victims of sexual harassment. However, the hashtag went viral only in 2017 when actress Alyssa Milano included it in a Twitter post saying, "If you've been harassed or sexually assaulted, write me #MeToo in response to this tweet." Her intention was to give visibility to a latent topic (Wolfe, 2018). From that moment, many international celebrities have shared their experiences using the same hashtag. The hashtag was also used by many other Twitter users.

In this context, it is important to investigate what issues arise around the powerful #MeToo movement. Such investigation can provide meaningful insights for companies and institutions and in terms of identification, awareness, and communication actions with regard to sexual harassment and women's inclusion. The results can also help

reinforce marketing and advertising messages supporting gender equality.

Accordingly, the main aim of the present study is to help companies and marketing professionals to better understand the challenges posed by the #MeToo movement through the analysis of publications shared by users on Twitter. The present study continues previous research by Manikonda et al. (2018) and Field et al. (2019). Along with these studies, our research highlights the need to investigate the topic sexual harassment in today's world.

Our overarching goal is to uncover practical implications of the topics and sentiments around the #MeToo movement for business and marketing, as well as to explore their theoretical importance for the theoretical investigations. Therefore, the primary purpose of this study is discovery, rather than hypothesis testing. We do not control the variables, but seek to discover them using exploratory analysis (Saura et al., 2019a). Therefore, the identified variables and indicators (in the form of topics with sentiments associated with them) could be used future studies as a starting point for the development of quantitative models that measure the influence of these variables on new hypotheses.

The remainder of this paper is structured as follows. After a review of relevant literature in (Section 2), in Section 3, we formulate the research questions to be addressed in the present study. Section 4 presents the methodology. Results are reported in Section 5. In Sections 6-7, we summarize the findings, draw conclusions, and discuss the implications of our findings for further research.

2. Literature review

Recent years have witnessed a dramatic growth in people's use of social platforms. All these users generate content to communicate with other social network users (Reyes-Menendez et al., 2018b). At the same time, this content is widely used by companies to get insights and knowledge about user purposes (Kulshrestha et al., 2015; Saura et al., 2019c), intentions, or feedback. Based on this information, companies can improve marketing and communication strategies on the Internet.

Twitter is among the most used social platforms to generate content on specific topics. This popularity of Twitter has made it a valuable source of data for many studies (e.g., Kulshrestha et al., 2015; Abbar et al., 2015; Chung et al., 2017). One of the main advantages of platforms like Twitter for research is that, on these platforms, users are organized in networks, which makes it possible to investigate groups of people, or communities, united by common interests, rather than individual profiles or personalities (Hubert et al., 2017). Accordingly, based in the data from social networks and digital platforms, it is also possible to identify influencers or opinion leaders, i.e. users who can lead a movement using different types of messages sent to the community and encouraging other users to follow them (e.g., Saura et al., 2019b). Likewise, based on the classification of content produced in response to specific causes, typically

Table 1. Social movements and their hashtags.

| Hashtag	Origin of the Social Movement	Category	Year
#FreeAJStaff	The aim of this movement was to free Al Jazeera journalists imprisoned by the Egyptian authorities between 2013 and 2015.	Terrorism	2013
#JeSuisCharlie	The death of Charlie and 12 other victims in the terrorist attack on Charlie Hebdo's office in Paris aroused empathy among millions of Twitter users.	Terrorism	2015
#BlackLivesMatter	The 17-year-old black youth Trayvon Martin was unarmed and killed by George Zimmerman who was acquitted a year later.	Racism	2013
#BlackExcellence	A video recorded in 2016 by black students of Science, Technology, Engineering and Math (STEM) went viral and has been used ever since to demonstrate the professional success of the Black people.	Racism	2017
#HeForShe	Created in 2014 by the United Nations (UN), this hashtag has been used by celebrities such as Emma Watson, UN Goodwill Ambassador, to fight for gender equality.	Gender Equality	2014
#MeToo	First used in 2006 by Tarana Burke on Myspace; in 2017, after a tweet by Alyssa Milano, the hashtag reached worldwide coverage and gave visibility to sexual harassment.	Sexual Harassment	2017
#TimesUp	Since 2018, this hashtag has also been used to refer to sexual harassment in the workplace.	Workplace Sexual Harassment	2018
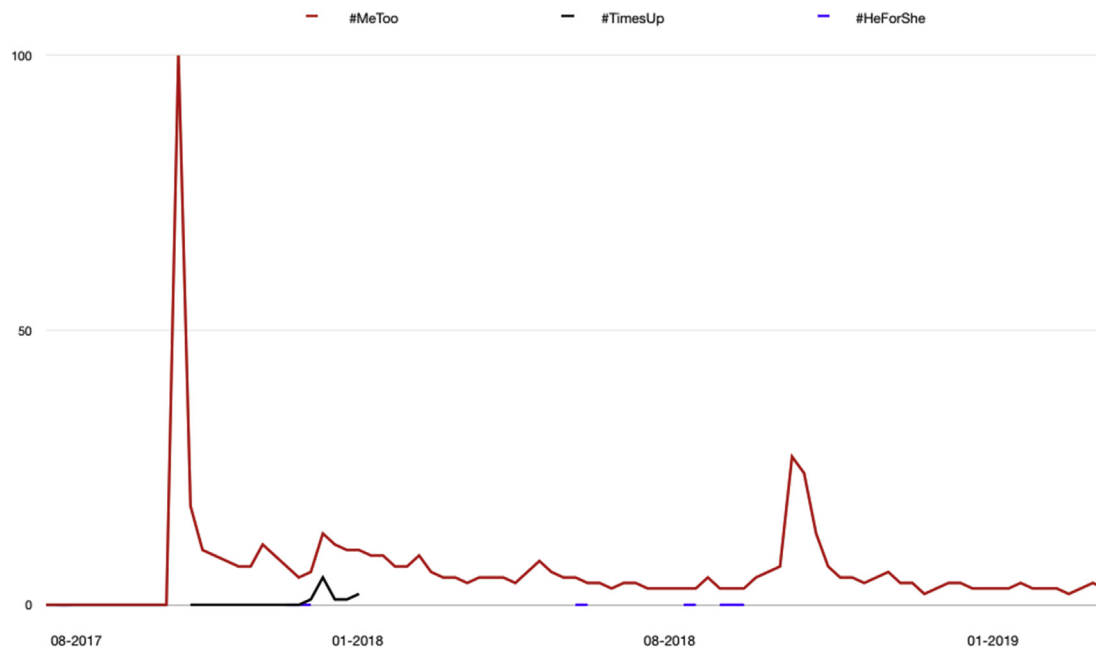
Figure 1. Evolution of searches on social movements using Google.

organized around hashtags (#), researchers can identify indicators and insights important for companies' digital strategy or pivotal to understand social movements (Stieglitz et al., 2018a,b).

Of note, through their comments, Twitter users can also influence the decision making of other users (Riquelme and González-Cantergiani, 2016). The aforementioned characteristics, along with the large amounts of data generated on the Twitter platform, have led many researchers to use the content generated on this social platform to obtain information on terrorism (Fischer et al., 2018), racism (Chaudhry, 2015), as well as on sexual harassment in private life (Kearl, 2018) and at work (Ward-Peterson and Chang, 2018). Likewise, the content generated on Twitter and other social networks was used to investigate social movements, such as #JeSuisCharlie (Sumiala et al., 2016) or #TimesUp (Ward-Peterson and Chang, 2018). Such analysis can thus be seen as an opportunity for improvement for companies, public institutions, and non-profit organizations (Stieglitz et al., 2018a,b).

Accordingly, investigating certain interest groups and their specific public objectives, such as women's groups in the #MeToo case, can add value to companies' business, communication, or marketing strategies. To this end, companies' messages should properly position those companies as positively oriented towards the aforementioned social movements (Brünker et al., 2020).

In order to makes sense of the data collected from social networks, different methodologies based on Natural Language Processing (NPL) have been used. For example, Saura et al. (2019a) used sentiment analysis to analyze, from the perspective of user feelings, user-generated content (UGC) related to Twitter-type startups. In this analysis, indicators in the form of key points for the development of a startup were extracted. This allowed the authors to establish that, in order to succeed (and be positively evaluated by users), startups should employ team leadership, technologies, and tools. Likewise, Reyes-Menendez et al. (2018a) used sentiment analysis and textual analysis to investigate users' perceptions of hotels expressed in users' TripAdvisor reviews. This allowed the authors to identify factors and indicators positively related to the quality of hotel services and sustainability policies. Similar methods of analysis were also used in the analysis of user-generated content related to social movements (e.g., Hysa and Spalek, 2019).

Along with sentiment and textual analyses, another technique to analyze UGC is using topics identification models, in which researchers apply algorithms to divide and categorize the UGC sample into sub-themes. These sub-themes can then be analyzed using additional algorithms based on NPL (Paschen et al., 2020).

One of the techniques globally used in the NPL is textual analysis where researchers analyze textual content with the focus on connotations, adjectives, or words that denote messages (Marengo et al., 2019). Finally, the types of analysis briefly reviewed above can also be meaningfully complemented by machine learning, data mining techniques, or other artificial intelligence tools. The advantage of the latter groups pf approaches is that training a machine to analyze data enables the analysis of more content (Krippendorff, 2013).

2.1. The #MeToo movement

The #MeToo movement has gained worldwide research interest since 2017. In a recent study, Johansson et al. (2018) highlighted the importance of why women in Sweden mobilized around the #MeToo movement more actively than women in Denmark. Specifically, Johansson et al. (2018) identified the following five factors that promoted the mobilization of Twitter users with regard to the #MeToo movement: (1) governmental support; (2) political opportunities; (3) culture; (4) framing processes, and (4) previous mobilizations. In another study that focused on the intentions of users who posted tweets about #MeToo, Wood (2018) classified user intentions into the following six categories: (1) solidarity; (2) narrative; (3) assertiveness; (4) objections, (5) activism, and (6) criticism. These results demonstrate the social relevance of the #MeToo social movement and its potential influence on different industries.

On the other hand, using topic-modeling techniques reviewed in Section 1, Clohessy (2018), identified the following three topics in the UGC tweets published by users: (1) criticism of women; (2) consequences of the movement for men; and (2) political impact of the movement. The authors concluded that these topics encompass the impulses and behavior of Twitter users towards providing their opinion on and support the #MeToo movement; similar conclusions were drawn by Saura and Bennett (2019).

Other authors sought to go beyond the identification of topics to investigate, using sentiment analysis techniques, the emotions of Twitter users expressed in corresponding posts. For instance, Manikonda et al.

(2018) analyzed the sentiments expressed in #MeToo tweets in order to understand users' attitude to this issue; the results yielded examples of negatively and positively connoted opinions that users shared about the movement. Likewise, Saura et al. (2018) identified the sentiment of the tweets to determine the attitude of users towards the subject of study. Other authors, such as Field et al. (2019), used affective analysis (a combination of topic identification and sentiment analysis) to study the #MeToo movement.

3. Research questions

Since the main aim of the present study is to gain a better understanding of #MeToo, a movement that originated from social networks (Manikonda et al., 2018), social platforms are our main research source (Strain et al., 2015). An important advantage of digital platforms is that, unlike traditional research sources (Abbar et al., 2015), the content on digital platforms has a network structure. Several previous studies analyzed social movements based on UGC in Twitter and classified this content according to sentiments expressed in corresponding tweets (Manikonda et al., 2018). In one relevant study, Field et al. (2019) used what they called 'affective analysis' to study sexual harassment, while Saura et al. (2019c) identified relevant topics and then performed sentiment analysis of the data. Therefore, social networks have become an information vehicle, a channel that can be meaningfully used by companies to support social movements or to fight against injustices (Field et al., 2019).

The first research question (RQ1) addressed in the present study is as follows: Can a social movement such as #MeToo be analyzed using Twitter-based UGC, and would such analysis reveal active agents that influence its development? Is it possible to analyze Twitter users' feelings related to and expressed in relation to #MeToo?

Furthermore, publications on Twitter are usually organized around common themes, known as topics (Culotta, 2014). In a previous study on #MeToo tweets, Wood (2018) analyzed user intentions and classified them into six categories. Likewise, Clohessy (2018) identified three different topics in a sample of tweets. The topics surrounding social movements in social networks can be used to determine the nature of these movements, identify key influencers, or study the behavior of society members (Drakett et al., 2018). The analysis of UGC topics in social networks can also be used to obtain helpful insights for companies or non-profit organizations to better understand their followers or target audiences and, therefore, to better informed about the ways to create appropriate and relevant messages for social network users (Palomino et al., 2016).

Accordingly, the second research question (RQ2) we address in this study is as follows: Can UGC topics surrounding the #MeToo movement on Twitter help companies to define messages that are inclusive and respectful to social movements, and by doing so, strengthen the companies' marketing, advertising, and reputational strategies?

Next, there is evidence that the analysis of Twitter-based UGC can help to better understand consumer behavior and expectations (Kulshrestha et al., 2015). The same applies to social movements such as the one against sexual harassment (Kearl, 2018; Ward-Peterson and Chang, 2018; Field et al., 2019). Therefore, the insights derived from UGC analysis can be used by companies to identify new target audiences, better understand each other, and find new ways to access these audiences (Chung et al., 2017)—all of which will help develop better marketing goals and messages. Several previous studies have already derived insights from Twitter-based UGC on different social movements therefore, such an approach can be relevant for the investigation of the viral movement of #MeToo as well. Accordingly, the third research question we address in this study (RQ3) is as follows: Can the analysis of Twitter-based UGC about the #MeToo movement provide companies with meaningful marketing insights about their consumers?

4. Methodology

4.1. Data sampling

Seeking to define UGC samples in social networks, Kim et al. (2013) and Pfeffer et al. (2018) indicated that UGC-based data are qualitative and, therefore, should be used for exploratory analysis, rather than for testing statistical significance of the variables. To solve this problem, several authors have proposed new sample construction methodologies (e.g., Piña-García et al., 2016). Therefore, we argue that UGC samples should be first analyzed for exploratory purposes, and only then evaluated statistically as presented by Saura and Bennett (2019). Accordingly, the purpose of the present study is exploratory, rather than hypothesis-testing (Kulshrestha et al., 2015). When determining the size of the sample necessary for our research on the tweets with the #MeToo hashtag, we took relevant previous research as reference points. For instance, in Saura et al. (2019b), the sample contained 35,401 tweets. Likewise, Palomino et al. (2016) analyzed 6,333 tweets with the hashtag #getoutside, while Reyes-Menendez et al. (2018a) focused on 5,873 tweets with the hashtag #WorldEnvironmentDay.

In the present study, we first extracted a total of 42,351 tweets; after filtering, the final sample amounted to 31,305 tweets. These tweets were in English and had #MeToo as the hashtag (Bologna and Hayashi, 2017; Palomino et al., 2016). #MeToo was the only search term used to collect tweets, because thus hashtag best matched our purpose.

Data collection was performed between February 1 and May 31, 2019. As tweets with the #MeToo hashtag appear more frequently in the periods of sexual scandals or harassment, which leads to an increase of the UGC related to these topics. We collected the data in the months when no specific scandal related to #MeToo occurred. This allowed us to obtain an adequate sample to investigate the engagement and conversations about this hashtag and to avoid social noise (De Choudhury et al., 2010; Gerlitz and Rieder, 2013).

For the data collection process, the MAC version of Python software 3.7.0 was used. After data collection, we filtered and cleaned the database using Python with Pandas software library. The initial sample was then cleaned to remove repeated tweets and retweets. Although retweets can express users' personal opinions, they can also contain negative statements about the topic, even though the same words are used in the hashtag. As this fact can distort the results, we did not analyzed retweets (Saura et al., 2019d).

Therefore, tweets with pure numbers were deleted (see Merle et al., 2019). Of note, tweets can contain either a hashtag (#) or a reference to a user profile (@). The replies were analyzed as independent tweets, considering the expressions related to the same subject under the same hashtag.

Images, videos, and multimedia content were not analyzed. Instead, we focused exclusively on text and analyzed it using natural language processing (NPL) (James, 2019). For filtering, we eliminated URLs that contained the tweets, as well as emoticons and special symbols that did not include capitalization or punctuation. Our decision not to analyze emoticons was based on the assumption that the analysis techniques used in the present study were not meant for the analysis of graphics or graphic icons and associated feelings (Sivarajah et al., 2017). Tweets shorter than 80 characters were also deleted. We used the commands of electing or replacing columns and indexes to reshape lost or empty values and to debug repeated or unnecessary data (Stieglitz et al., 2018a,b).

In addition, following Saura et al. (2018), the sample was validated using the following four quality criteria: (1) Twitter profiles had to have been active during the last 3 months; (2) Twitter profiles had to have a profile photo and a cover photo; (3) Public profiles had to have used the hashtag #MeToo; (4) Tweets had to have the minimum length of 80 characters. These criteria were applied in order to increase the quality of the tweets in the database. Accordingly, our dataset did not contain the tweets from spam profiles or robots that duplicate content using fake profiles (Reyes-Menendez et al., 2019).

4.2. Identification of topics with the LDA model

In order to identify the topics, we used the LDA model. This model is based on the mathematical and probabilistic assumption and unfolds in several steps (Jia, 2018; Saura et al., 2018). LDA was created by Pritchard et al. (2000) as an analysis technique based on machine learning. Subsequently, LDA was improved by Blei et al. (2003). Using the LDA model, in the first step, our objective was to identify keywords in the database. Each word was encoded in a separate document. Then, using the identified keywords, we performed an identification of the topics. Finally, the identification of the most relevant topics within the UGC dataset was performed (Saura et al., 2018).

This identification of topics can be performed only using the LDA model, as the topics cannot be identified *a priori* (Jia, 2018). Therefore, the LDA makes it possible to identify the relationships between variables that are not observable.

4.3. Sentiment analysis

After topic identification, we used an algorithm developed in Python to classify tweets according to sentiments expressed in them. The Sentiment Analysis (SA) approach, also known as Opinion Mining (OM), relies on using the systems that can detect the feelings expressed in a text or textual content—in our case, the tweets with the hashtag #MeToo. For the development and use of the SA approach, several training approaches are available. For instance, interfaces can be used to improve the algorithms that work with machine learning. There are also techniques that develop SA with artificial intelligence or hybrid models that require both the machine learning technology and data-mining training. According to Saura and Bennett (2019), the choice of emotions analyzed in textual content depends on the specific research purpose. For instance, SA can be used analyze all kinds of emotions, such as joy, sadness, anger, happiness, and fear (Pritchard et al., 2000).

Overall, there are three groups of approaches based on SA. The first group consists of rule-based approaches where the analysis of feelings expressed in text is based on a set of manually created rules (Pfeffer et al., 2018). The second group embraces automatic approaches where machine learning is used to understand the data. The third group includes hybrid approaches, i.e. approaches that combine both rule-base and automatic approaches. Typically, rule-base approaches are characterized by some type of scripting language that identifies subjectivity or polarity (Merle et al., 2019). The classifiers developed in the present study belong to NLP techniques, such as stemming, tokenization, parsing and lexicons, among others. We also used an algorithm that receives text as input and returns, as output, the categories defined by positive, negative, or neutral characteristics (Krippendorff, 2013).

Since the model learns from the inputs classified with data mining, thereby indicating to the algorithm that works with machine learning how to classify subsequent inputs (Krippendorff, 2004), the algorithm can be trained. Such SA algorithms are known as support vector machines (SVM); the more times they are trained, the greater the success of their results (see Saura and Bennett, 2019). SVM are non-probabilistic models where the representation of the text that composes the sample, in this case tweets, includes examples of classification in categories improved with machine learning. There are also algorithms based on Naïve Bayes; the Bayes' Theorem is used to predict categories or linear regression where statistics are used to classify the contents.

In the present study, we used an SVM manually trained on 2539 samples selected using a randomized controlled process (Sherman et al., 2005; Banerjee et al., 2015). To verify reliability of the results, Krippendorff's (2004) alpha value (KAV) was calculated (see Section 5.2).

4.4. Textual analysis

Finally, we performed textual analysis with the NVivo software to identify the most frequently used terms in the downloaded tweets. The process of data entering in NVivo was performed manually, even though the database was already organized by sentiments using the trained algorithm (see Section 4.3). Despite the availability of other Python libraries based on data mining to perform TA, in the present study, we decided to use the NVivo text analysis tool, because it has a simple interface that can be easily used in the marketing environment to perform individual research; alternatively, it can be added to other database analysis processes (Sherman et al., 2005).

Based on these considerations, we organized the information contained in the tweets in nodes and proceeded to filter and clean the database (Krippendorff, 2013). All connecting elements and prepositions were eliminated (Saura et al., 2018) to obtain only words in the analysis. The next step was the classification of the words into three nodes: N_1 (positive), N_2 (negative), and N_3 (neutral). This classification yielded a descriptive and clear organization for further exploratory analysis divided into three types of sentiments. We also computed the weighted percentage (WP), i.e. the weight of each indicator of the nodes, according to the number of times each of words repeated in the database. To calculate this proportion, the qualitative analysis software NVivo was used to perform specific searches in the text to find the terms linked to that specific search within the selected node. The value of WP corresponded to the relevance of the tweets in the selected database. The results of the analysis of the WP indicators relative to each node in the database helped to identify the topics or words with a greater weight linked to marketing or other classification.

Figure 2 shows the four stages of the analysis discussed in Sections 4.1–4.4 The first stage (panel "Twitter UGC") included the process of extracting and collecting data from the Twitter API. In the second stage (panel "Topic Identification"), the LDA model was applied to the dataset containing the final sample of 31,305 tweets. In the third stage (panel "Topic Sentiment Identification"), SA was applied to the results of the LDA to divide these topics into positive, neutral, and negative feelings. Finally, in the fourth stage (panel "Textual Analysis"), textual analysis was applied to analyze identified indicators.

5. Results

5.1. Latent Dirichlet Allocation (LDA) model

After the analysis with the LDA model, seven topics linked to the #MeToo movement were identified (see Table 4). During this process (see Jia, 2018; Saura et al., 2018; for further detail), the keywords corresponding to each of the sentiments in topics were categorized. On finding 10–20 keywords, these words were used to formulate the topics (see Table 2). In this process, to the goal was to formulate a phrase that contained 10 most repeated words and try to order them to make sense. Thus, the name of the topic was the result of the combination of these phrases and the formulated content.

The identified topics provide important insights about user behavior and their perceptions of the #MeToo movement. Accordingly, companies can apply this new knowledge in their marketing and advertising strategies via digital channels. Table 2 shows the identified topics and their descriptions.

5.2. Sentiment analysis

After training the algorithm with Python, we performed the complete analysis of the sample of extracted tweets. At this point, in order to calculate the accuracy of the algorithm, we used a metric known as Krippendorff's alpha value (KAV), one of the most popular metrics to measure reliability in SA (see Saif et al., 2013). The KAV indicates the accuracy and quality of algorithm success. Krippendorff's value can have the following three categories of reliability. The first category ($\alpha \geq 0.800$) is high reliability. With these results, the authors can make robust conclusions. The second category ($\alpha \geq 0.667$) suggests tentative reliability, so such results are exploratory, and only tentative conclusions can be
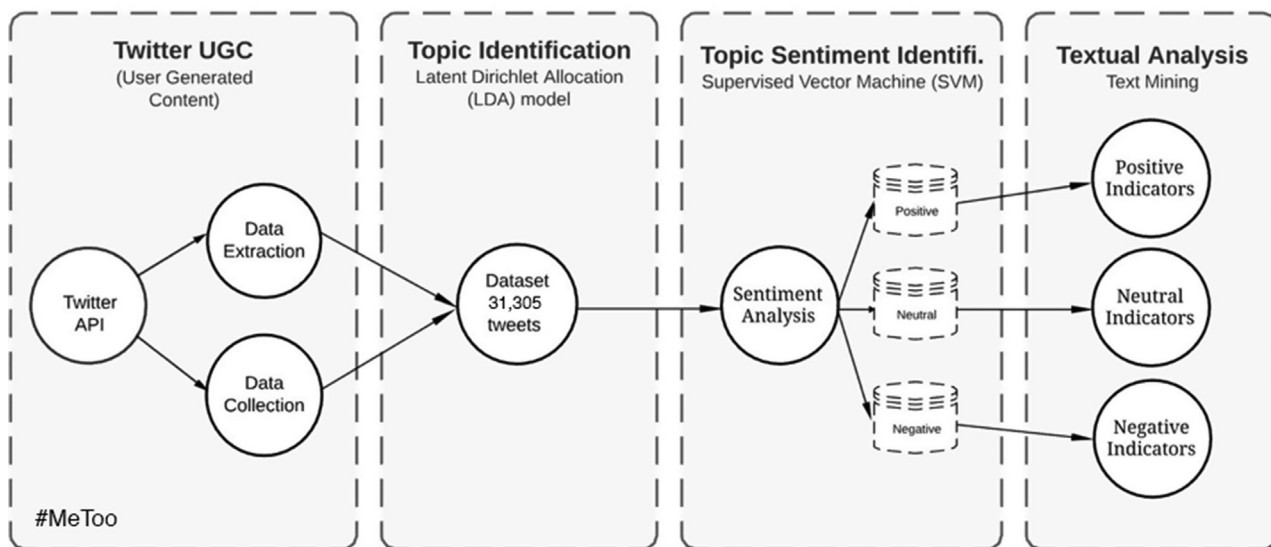
Figure 2. Steps of the analysis.

Table 2. Description of topics related to #MeToo.

Topic name	Topic Description
Public Figures	Tarana Burke started the movement that was later supported by Alyssa Milano and that reached RealDonaldTrump or Melania Trump against defendants such as Thomas Frieden or Harvey Weinstein.
Sexuality	Victims of sexual harassment who prosecute their abusers
Politics	Politicians of all types (from Liberals to Republicans or Democrats, Left or Right) involved in the movement
Female Topics	Women stand together for feminism, females, girlfriend
Media	The stories across the Internet, Hollywood actresses, media and the news, such as NY Times and CNN
Other Hashtags	The #MeToo movement's relation to #Timesup, #BlackLivesMatter, #GenderEquality, and #WomanEqualityDay
Business	Educators as leaders of equality in career, work, and at the workplace

made. Finally, the third category ($\alpha < 0.667$) is low reliability, suggesting that the algorithm can be improved through training with more samples (Krippendorff, 2004).

In the present study, the average KAV was 0.694. With regard to positive feelings, KAV values were 0.697, 0.754, and 0.734 for positive, neutral, and negative feelings. Of note, an important step in the training of the algorithm was the identification of irony and sarcasm in the comments used for the training. During this process, the comments that were not linked to the #MeToo movement were removed from the sample and from the training phase of the algorithm.

The remaining topics were classified according to sentiments expressed in them (as positive, negative, and neutral). Importantly, although the SA may have more categories of feelings, in the present study, we decided to use positive, negative, and neutral feelings, because it is the standard basis of SA algorithms usually used for exploratory studies (Saura and Bennett, 2019); however, future studies may use additional feelings, such as surprise, happiness or anger, among others (Yi et al., 2003) to verify or improve our results.

On identification of the sentiments in the complete sample of tweets, the topics obtained through the LDA model were classified according to the sentiments expressed in corresponding tweets.

Importantly, the sentiment of each topic encompasses the context surrounding each of the words that make up this topic. Accordingly, the identified words and topics may be used in companies' marketing and advertising strategies on digital channels. For example, the topics that were identified in the present study as such that are associated with positive feelings can be used by companies to elicit positive perceptions and evaluations on part of their target audiences. However, with regard to negative topics, companies should take into account that the words

that compose those topics could cause (in appropriate contexts) reputation problems if their messages have too compromising or risky connotations, or if they are linked to social movements such as #MeToo.

Table 3 shows the identified topics, corresponding words, sentiments, and respective KAV values.

As can be seen in Table 3, Public Figures, Sexuality, and Politics were associated with negative sentiment; Female Topics were associated with positive sentiments, and, finally, Media, Business, #MeToo and other hashtags were associated with neutral feelings.

5.3. Textual analysis results

To perform textual analysis (Moro et al., 2016), the corresponding nodes were used with each of the sentiments identified in the previous step, Sentiment Analysis. Using the NVivo software, we obtained the following three nodes: N_1 (positive), N_2 (negative), and N_3 (neutral). These nodes corresponded to the three types of sentiments (positive, negative and neutral). Next, each of the seven topics was coded.

Finally, the most frequently used terms in the topics classified by nodes were classified according to their sentiment. The number of times each of the words appeared in the sample was counted. This measure was called Count (see Tables 4, 6, and 8). In addition, we also qualitatively analyzed each independent tweet within its topic. In this step, we identified additional keywords contained in each topic, assigning a relevance value (WP) to it with respect to the total sample. These results can be meaningfully used by companies to categorize robustness of either positive or negative connotations of their messages. Likewise, companies can use these results to identify a list of stop words that should not be used in companies' marketing and advertising strategies using digital channels.

Table 3. Topics, keywords, and sentiments.

Topic	Keywords	Sentiment	KAV
Public Figures	Asia Argento, Keith Ellison, Melania Trump, Tarana Burke, Thomas Frieden, Alyssa Milano, RealDonaldTrump, Harvey Weinstein, RoseMcGowan, Hollywood	Negative	0.734
Sexuality	Rape, Abuse, Beat, Accused, Assault, Victims, Sex, Violence, Harassment	Negative	0.734
Politics	Republicans, Liberals, Left, Right, Politician, Democrats	Negative	0.734
Female Topics	Woman, Girlfriend, Female, Feminism, Together	Positive	0.697
Media	Stories, News, TheMedia, Actress, Movies, CNN, NY Times, Internet, Twitter	Neutral	0.754
Business	Forward, Educate, Educators, Leader, Workplace, Work, Career, Equality, Advertising	Neutral	0.754
#MeToo, Other Hashtags	#TimesUp, #BlackLivesMatter, #GenderEquality, #WomensEqualityDay	Neutral	0.754

Table 4. Results for N_1 (positive indicators).

N_1	Similar Factors	WP	Count
Female Topics	women, woman, girl, girlfriend, love, loving, gender	2.18	7097

Tables 4, 6, and 8 show the topics with similar factors, WP and Count, while Tables 5, 7, and 9 provide examples of the analyzed tweets according to the tweet ID, user, date, and description of tweet indicators.

To better visualize the results discussed above, Figure 3 shows a tag cloud where the keywords are represented according to their frequency in the dataset (Sinclair and Cardew-Hall, 2008). As can be seen in Figure 3, the standard hashtag of the movement is in the center, surrounded by the names of different public figures associated with the movement (e.g., *KeithEllison, TaranaBurke*), terms related to sexuality (e.g., *harassment, victims*), the media (*Twitter, Internet*), gender (e.g., *woman, girlfriend*), and business (e.g., *leaders, advertising*).

6. Discussion

In recent years, the #MeToo movement has acquired a great media visibility and coverage both in traditional media, such as TV, and in digital media, such as in the Internet or social networks like Twitter (e.g., Johansson et al., 2018; Fox, 2019). This movement against sexual harassment is strongly related to individuals, is very politicized, and focuses on violence and abuse. These two concepts have negative connotations, and many social agents fight against violence and abuse-related situations in online communities, through influencers in social media or generating UGC (Youmans and York, 2012).

In the #MeToo movement, individuals who have experienced sexual harassment become the tangible target of user comments, particularly on Twitter. That is why the named victims (as well as perpetrators) become the subject of numerous comments that spread much faster than in a traditional court trial aimed at clarifying whether the accusations are real or fictitious. Notable in this regard are the names such as Tarana Burke, creator of the movement, Keith Ellison, accused, or Asia Argento, victim and accused. In addition, Keith Ellison is a Republican, so there emerges a negative political linkage.

As demonstrated by Jackson et al. (2009) and Eshuis et al. (2014), companies' advertising and marketing campaigns often have ideological connotations. In this context, and in the #MeToo era, certain practices of product promotion by companies, either in traditional media or online, are not acceptable. One example of such unacceptable practices comes from Hollywood film advertising where women are shown as objects of sexual desire—to a point where we cannot see their faces or even their heads in an ad, because only their body and silhouette are used to attract the viewers' attention. Discontentment with this type of advertisements has led to the emergence of another movement around the hashtag #HollywoodHeadless. In this movement, people bring to public scrutiny advertisements where women's body is the main focus of attention. Interestingly, despite the negativity of the stories that spurred the movement, it has also had a positive impact on the society. Specifically, it has led companies to recognize the importance of gender equality-oriented practices, such as the inclusion of more women behind the scenes in Hollywood films or gender-neutral practices in advertisement production.

Therefore, in a work environment that abounds in sexual harassment of women, companies use social movements such as #MeToo to demonstrate that they support gender and labor equality. In addition, in the digital ecosystem which people use daily to claim their rights, equality, and justice (Carty and Barron, 2019), company executives and managers should take care to implement adequate advertising and marketing practices. Abusive strategies that use women for advertising purposes or posit them as submissive to men are now in the past. In this respect, Chowdhury et al. (2019) demonstrated how such abusive actions and campaigns can negatively affect companies' online reputation and marketing strategies.

As demonstrated by the results of the present study, the #MeToo movement goes far beyond Twitter and illegitimate practices such as sexual harassment. It expands to other social media, to other social movements such as #TimesUp and #TimesUpAvertising, and helps users denounce biased gender practices, such as gender discrimination in the workplace.

Companies' advertising and marketing strategies should be based on gender equality and respect of the social rights of all individuals. Accordingly, executives must develop social media strategies that respect women and be aware that their online channels are public social agents that can drive change (Allcott et al., 2019). Therefore, in using online channels, companies should combat sexist advertising, as well as avoid sexual harassment and other social forms of injustice. As demonstrated by our results, as well as those reported by Becatti et al. (2019) and Zannettou et al. (2019), such actions will help companies to be positively viewed by social network users involved in social movements, which will contribute to companies' online reputation in the social media.

Table 5. Examples of tweets with positive sentiment.

Tweet ID	User name	Dates	Tweet description
919	@BBHblacksheep	2018-07-21 18:11:50	@CreativeReview talks to Sarah Watson, Chairman of BBH New York and a member of #TimesUpAdvertising about the changes caused by #MeToo in the US and what needs to be done
1329	@LeadingWPassion	2018-07-26 12:08:13	Why are gender equality and the empowerment of women essential for preventing violence against women? https://t.co/TcLhgNlqpk

Table 6. Results for N$_2$ (negative indicators).

N$_2$	Similar Factors	WP	Count
Public Figures	Tarana Burke, Melania, RealDonaldTrump, Hollywood	2.81	9114
Sexuality	Victims, Assault, Harassment, Sexual, Abuse	2.06	7968
Politics	Democrats, Dems, Liberalism, Liberal, Rights	0.97	3169

Table 7. Examples of tweets with negative sentiment.

Tweet ID	User name	Dates	Tweet description
21325	@politicalrod	2018-08-26 15:58:48	To the advertisers on the @TheAMShowNZ you aren't reaching me #MeToo #rights
24666	@HlywoodHeadless	2018-08-27 18:06:07	Not only are women of Hollywood headless, but they are also silent. Most marketing and projects

Table 8. Results for N$_3$ (neutral indicators).

N$_3$	Similar Factors	WP	Count
Media	Internet, Twitter, Stories	0.67	2139
Business	Advertising, Forward Education, Leaders	0.6	1933
#MeToo and Other Hashtags	#Metoo #MeTooNatSec #TimesUp #TimesUpAdvertising	4.44	14.427

Table 9. Examples of tweets with neutral sentiment.

Tweet ID	User name	Dates	Tweet description
20250	@campaign_purple	2018-08-2610:12:46	As the co-author of the #MeTooNatSec Letter and the founder of the @womensfpnetwork, @jenna_dc brings invaluable leaders.
18211	@firebrnd13	2018-08-16 10:27:36	Now that's top notch #advertising @Intel. Captures the heart, popular sentiment around #MeToo, beauty, #art, and so https://t.co/loB7rYw1Zs

Figure 3. Tag cloud obtained in the NVivo analysis.

7. Conclusions

The present study aimed to analyze the #MeToo movement so that to help companies and marketing professionals to better frame their communication and advertising actions with regard to sexual harassment. To this end, we analyzed a dataset containing 31,305 tweets with the hashtag #MeToo using a three-stage methodology.

Our first research question was as follows: Can a social movement such as #MeToo be analyzed using Twitter-based UGC, and would such analysis reveal active agents that influence its development? With regard to this question, our results demonstrate that the analysis of Twitter-based UGC can be meaningfully used to identify active agents of the #MeToo movement. Also, using sentiment analysis, we have linked these active agents and public figures to the feelings these figures are associated with in UGC, demonstrating which public figure or agent causes each feeling.

Our second research questions concerned the usefulness of Twitter UGC topics surrounding the #MeToo movement for companies in terms of defining relevant messages and strengthening the companies' marketing, advertising, and reputational strategies. In this respect, our results have helped us to identify the main topics that structure the #MeToo movement on Twitter. We found seven main topics organized into three groups depending on the sentiments: (1) Female Topics (positive, accuracy 0.754); (2) Public Figures, Sexuality and Politics (negative, accuracy 0.734); and (3) Media, Business, #MeToo, and other hashtags (neutral sentiment, accuracy 0.697). These topics should be carefully considered by companies in their marketing and advertising campaigns, as well as in their social media strategies. Companies should also be aware of the fact inappropriate social media actions can damage their digital reputation. For example, if online community users perceive that companies' marketing communications are not inclusive and respectful to both genders (or that they do not spread neutral messages linked to political parties or ideologies) in Twitter, these perceptions can have a detrimental impact on companies' digital reputation.

The third research question we addressed in this study was whether the analysis of Twitter-based UGC about the #MeToo movement can provide companies with meaningful marketing insights about their consumers. In this respect, according to our results, we found that the #MeToo movement is closely linked to politics. Many of the parties involved in sexual harassment cases are public figures, so the debates inevitably become politicized. Consumers side with any of the party in such conflicts depending on their ideology and context. We can also conclude that the #MeToo movement is a very media-centered movement that starts from Hollywood itself, linking actresses, producers, and advertising campaigns to promote films as analyzed in Twitter. This combination of elements is tremendously attractive for consumers in

social networks, since many of the defenders or detractors are public figures with influence in social networks.

However, the negativism around #MeToo movement has created a critical spirit among consumers who no longer wait for legal measures and denounce a situation if they consider it unfair, using social platforms with the hashtag #MeToo.

In this way, instead of negativism, we find a neutral space in which one can become a leader, educate others, and tell emotional stories in the #MeToo community on Twitter. One of the key aspects for consumers is that each person behind the #MeToo movement has a story, and this is closely related to storytelling in social networks and their interactions in this kind of digital environments.

7.1. Theoretical implications

The results of the present study offer meaningful theoretical implications for individuals, organizations, companies, and institutions. Specifically, our findings underscore the importance of gender equality, gender equality at work, mobilizations in social networks and, more specifically, in the #MeToo Twitter community. In addition, the identified topics could be used in future research as independent constructs or variables to be studied in quantitative models whose significance with respect to other topics can be measured.

Likewise, our results also demonstrate that the #MeToo movement has marked the beginning of a social movement when users show a great predisposition to denounce what they consider unfair or what does not meet the standards of gender equality on social media. These implications may be the starting point for future research focused on the study of social movements, sociology, sexuality, or machismo in work environment on Twitter. Finally, the methodology used in the present study can be replicated in future studies to either further investigate the #MeToo movement or to analyze other social movements, such as #TimesUp or #TimesUpAvertising, among others.

7.2. Practical implications

First, companies should be careful about how they formulate the link between their brand and the #MeToo movement on Twitter, since, in the era of #MeToo, disinterested or sexist actions that posit women as objects can become viral visual elements that link the company with socially inappropriate activities or actions in social media.

Second, users want companies to assume the responsibility to respect the values promoted by the #MeToo movement online. Therefore, contrary to previously widely held view that using sexism in advertising can be a convincing and effective strategy to attract consumer attention (Glick et al., 2000; Hammond et al., 2018), advertising campaigns in the #MeToo era should become more inclusive, educate society on the #MeToo values, and show women in leading positions.

Therefore, informed by the results of the present study, CEOs and advertising managers of small and large companies can improve the practical management of their companies and social media campaigns to make them more sensitive to gender-equality issues and concerns when planning their communications on Twitter.

7.3. Limitations and future research

In the present study, we used processes based on machine learning manually trained in previous research. Furthermore, with regard to the application of the LDA, although it is a mathematical model, qualitative intervention is needed for the selection of the names of the topics. It should also be taken into account that machine learning and SVM-based algorithms are subject to daily improvements, leading to an increase of their KAV.

Future research can analyze the topics identified in the present study or extend the analysis undertaken in the present study to other social movements on Twitter. In addition, future research may validate our

insights by conducting, for example, interviews in business environments, surveys, or focus groups.

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