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How Do I Feel? Identifying Emotional Expressions on Facebook Reactions Using Clustering Mechanism

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ABSTRACT The recognition of emotions and feelings through computer technology and devices has been widely explored in recent years. Social networks have become a natural environment in which users express their feelings and opinions through social media, and this includes their Facebook reactions. The aim of this study was to investigate whether the emoticons have chosen by users in social network news actually express the emotions they wish to express, having as indicative, the polarity of the emotions, and the six basic emotions. The data collection was carried out following three courses of action: 1) survey of the posts with higher reactions rates of popular news pages; 2) selection of news by a panel of experts to verify its reliability; and 3) identification of reactions, polarity, and basic emotions flagged by Facebook users for each news item. Finally, an Expectation-Maximization algorithm was deployed to find the relationship between the reactions and the basic emotions signaled. The results made it possible to determine the polarity and the correlation of the reactions with the emotional expressions. This suggests that the use of reactions in feelings analysis algorithms can increase the confidence in determining the emotion that the content reflects and the emotional state of the social network users.

INDEX TERMS Facebook reactions, emoticons, recognition of emotions, emotional state, sentiment analysis, social media, social networks, clustering.

I. INTRODUCTION

Social networks, such as Facebook and Twitter, have changed significantly as people live. Thus, it has become a habit to share and record daily life online. The large sharing of data in social networks has allowed the realization of several studies to analyses of human behaviour [1]–[5]. The use of these online communities is due not only to facilitate of access but also to the fact that these social networks have become an environment in which users feel more comfortable to share their particularities such as their ideas, thoughts and opinions. Thus, the fact is that shared content online, such as texts, images, videos, emoticons and other forms of interaction, has become another lens to be considered by mental health professionals, that is, a new interaction environment to be used for the observation of behavior and social interactions. In the context of social interactions, the expressions of emotions have as functions to provide information about how they feel, regulate interaction and establish intimacy [6]; thus, people use these expressions to communicate that they feel joyful, sad, angry, and even to understand the reaction of others in different situations [7], [8]. Expressions of emotions are studied by some authors in various countries [7], [9], and particularly Paul Ekman has devoted himself to the study of recognition of facial expressions as emotion flags [8], [10], [11]. In a survey of research conducted by his group and other researchers in 21 countries [11], in which participants were exposed to photos and in the sequence should indicate the perceived emotion, the author showed that there was an extraordinary agreement among

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photos of facial expressions and perceived emotions, when comparing the results of the studies between these countries. The emotions focused in the studies were anger, disgust, fear, joy, sadness and surprise, then named as basic emotions. The studies led Ekman to conclude that the recognition of basic emotions is similar between different countries and cultures of the world.

Expressing and recognizing emotions is, however, an important skill for social performance [6], and therefore the recognition of emotions in face-to-face interaction is widely studied [7]–[11]. However, few studies have shown how much this experience of expressing emotions can actually be transposed into the interactions that occur in social networks [12] such as Facebook or Twitter, which are now the most widely used media. There are about 2.07 billion active users of Facebook [13], who spend most of the day online, making the virtual environment a rich source of data about what users think and feel [14]. In this type of interaction users often adopt the use of emoticons in posts, messages and comments to increase the meaning of these messages and express emotions with symbols without the need to write. Emoticons are small images or combinations of diacritical symbols, intentionally developed to replace non-verbal components of communication, suggestive of facial expressions [12], [14].

The frequency and relevance in the use of emoticons have been the subject of analysis in several recent studies: [15]–[18]. Researchers have explored the use of emoticons in various areas: addressing mental health problems; reactions to stressful events; preferences for brands or policy choices; and various opinion polls [14], [19], [20].

Emoticons are ways of communicating feelings and even adding textual information to a social network [21]. However, few studies have explored the relationship between emoticons and textual information [16], [18], and even fewer to the relationship between emoticons and the expression of feelings or sentiments [17]. While it is claimed that emoticons and, most likely, reactions, can be used to express users' emotions, there have still been few studies that investigate whether they actually reflect them.

One way to determine this is by analyzing the polarity of emotions by means of emoticons; that is, to classify sentiments in positive, negative or neutral states. One method adopted by some studies to understand the meaning transmitted by the emoticons, was to connect them with words through a lexical analysis of emotional feelings by means of finite state machines (i.e., by taking account of all the history of textual production by a particular user, from the oldest to the most recent posts). The attribution of the polarity of emotion could be a useful method of classification because it allows a better grasp of how to conduct a sentiment analysis since the specific attribution of each emotion is quite complex; however, the relationship between polarized sentiments or emotions is not always clear.

Facebook has created a set of emoticons called reactions, to enable its users to react to the contents of the network,

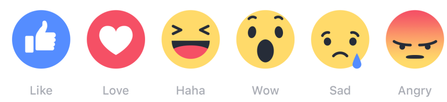

FIGURE 1. **Facebook reactions.**

such as posts and comments. The reactions defined by the network were: *Like, Love, Haha, Wow, Sad and Angry* as Figure 1. This study aimed to investigate the following:

1) ***How*** *these* ***reactions*** *are employed in the* ***classification of polarity*** *(positive, negative and neutral)*?
2) ***How*** *are described the* ***correlation*** *between the* ***reactions*** *used in Facebook (virtual expression of form) and the* ***emotions*** *(forms of expression in a real environment) can* ***express emotions*** *and to be* ***described as basic emotions*** *?*

Paper Outline: The remaining parts of this paper are organized as follows. Section 1 presents the related work about the recognition of emotions using emojis or emoticons. Section III presents the methodology and materials used. Section IV the results of the analyzes that answer the research questions. Section V the discussions of the results from the computational and psychological point of view. Finally, in Section VI the final considerations.

II. RELATED WORK

This section presents the works most related to this study, that is, that perform the recognition of feelings and emotions in virtual environments, through the use of emoticons, emoji or similar. The works are indexed in the main research bases and are presented briefly in a chronological way in order to show some of the problems addressed, as well as to direct to the research gap. addressed in this work.

First, E. Kouloumpis, T. Wilson, and J. Moore [22] researched the utility of semantic features for recognizing sentiment in twitter messages. They assessed the convenience of existing lexical assets (utilized in works with e.g., in [23], [24]) just as features that catch data about the casual and inventive dialect utilized in micro-blogging. They utilized a hashtag and emojis dataset and utilize an assortment of features for classification tests utilizing n-grams and vocabulary features, acquiring a normal F-measure of 0.65 to 0.68 and an accuracy of 0.74 to 0.75.

In study [25] was to find the mentality or supposition of the tweets, which is normally figured as a machine learning based content order issue. They utilized two strategies for investigations conclusion: First, physically marked (LM) information to prepare completely regulated models; Second, a novel model, called emojis Smoothed dialect demonstrate (ESLAM), to deal with this test. The essential thought was to prepare a dialect display dependent on the physically named information and after that utilization the loud emoji information for smoothing. One aggregate of 3727 tweets was assessed. Around 570 tweets were with valence positive and 654 negatives. 2503 was with unbiased messages. In the wake of expelling the re-tweets or copies and setting the classes to be adjusted, we arbitrarily pick 956 tweets for extremity characterization, including 478 positive tweets and 478 negative ones. For the subjectivity order, we likewise set the classes to be adjusted and haphazardly pick 1948 tweets for assessment, including 974 abstract tweets and 974 targets (nonpartisan) ones. The ESLAM demonstrate accuracy 0.79 to measure the impact of the emoji.

Zhao *et al.* [26] testing the effectiveness of a framework called MoodLens. In MoodLens, 95 emojis are mapped into four classes of emotions, for example angry, disgusting, joyful and sad, which fill in as the class names of tweets. Therefore, the authors extract over 3.5 million tweets that contain emojis. It shows that in Weibo, there is about 5% of the tweets named by the sentiment emojis. At long last, they acquire 569,229 sad tweets, 290,444 appalling tweets, 2,218,779 joy tweets and 607,715 sad tweets. These tweets could be utilized as an underlying sentiment corpus for Weibo. For each tweet t in T, MoodLens changes over it into a grouping of words wi, where wi is a word and i is its situation in t. In this demo, it is utilized a standard pack of words as the element, set $ft = 0.9, P(cj) = 0.25$ and get a Naive Bayes classifier, its accuracy is 64.3%, the precision is 53.3% and F-measure is 58.3%. The discoveries propose that sentiments varieties are all around caught by MoodLens to viably recognize irregular occasions in China and can be arranged for Naive Bayes, a high classification accuracy.

In [27] it was proposed an unsupervised sentiment analysis with characters that together seek to represent emotions. For this, it was investigating whether the signals digraphs can potentially help sentiment analysis by providing a unified way to model two main categories of emotional signals, i.e., emotion indication and emotion correlation. The method was based on the comparison of the proposed framework with the state-of-the-art methods on two Twitter datasets and empirically evaluate our proposed framework to gain a deep understanding of the effects of the emotional signal.

Hogenboom *et al.* [28] analyze how the emoticons convey sentiment. Therefore, they utilized a physically made emoji estimation dictionary so as to enhance the cutting edge vocabulary based assessment grouping strategy. They were assessing the methodology on 2,080 Dutch tweets and gathering messages, which all contain emojis and have been clarified for a conclusion. On this corpus, section level representing estimation inferred by emojis fundamentally enhances slant characterization precision, wherein with 22.02 % right grouping without Emojis and 93.94% of exactness with emojis.

In the [29] study it was described the estimation of short casual literary messages, for example, tweets and SMS (message-level assignment) and depicted the opinion of a word or an expression inside a message (term-level undertaking). The framework is dependent on a directed factual content characterization approach utilizing an assortment of surface shape, semantic, and notion features. The sentiment features are fundamentally gotten from novel high-inclusion tweet-explicit sentiment vocabularies. These dictionaries it was consequently created from tweets with assumption word hashtags and from tweets with emojis. To enough catch the assumption of words in refuted settings, a different estimation dictionary is created for discredited words. The framework positioned in the SemEval-2013, acquiring an F-score of 69.02 in the message-level undertaking and 88.93 in the term-level undertaking. Post-competition enhancements support the execution to an F-score of 70.45 (message-level assignment) and 89.50 (term-level task). The creators exhibit that the utilization of the naturally produced vocabularies results in execution additions of up to 6.5 absolute rate focuses.

Vashisht and Thakur [14] looked to portray how emojis can be identified with opinions and are a valuable method for investigating how to discover the extremity of the assessment passed on by the content. They investigated 1,250 statuses and 2,050 remarks on Facebook Internet-based life. The examination demonstrated that the utilization of a limited state machine for emoji inputs was an extremely proficient method for surveying the feeling communicated by the related content. The outcomes validate the way that emojis can be of essential significance when examination sentiments in PC interceded correspondence.

In [30] study the objective was to investigate if there is emotional content in an emoji and what is the kind of content emotional. For this, it was proposed the main emoticon sentiment vocabulary, called the Emoji Sentiment Ranking. The authors draw a map of the 751 most as often as possible utilized emoticons (Pearson 0.9 and spearman 0.8 correlation). About 4% of the commented-on tweets contained emoticons. The Welch's test-t contrasted tweets with and without emoticon (with the $p - esteem \approx 0$) they can conclude, with high confidence that the tweets with and without emoticons have fundamentally unique assessment implies. Furthermore, the tweets with emoticons are altogether increasingly positive ($mean = +0.365$) than the tweets without emoticons ($mean = +0.106$). The outcomes recommend that tweets with emoticons are all the more sincerely stacked and tweets with emoticons facilitate the prevision of the estimation.

Wang and Castanon [17] compiled a list of 164 emoticons, which have been used both in previous studies and by Wikipedia, and carried out searches to find out how they were used in a large dataset of collected tweets, over the period of a month, through the Twitter Decahose API. The aim of this study was to describe the use of emojis and their links with Sentiment Analysis, particularly with regard to polarities. The results showed that the emoticons that are most often employed by users, appear to be more reliable predictors of a polarity-feeling. In the case of the emoticons ":)" (allusion to the happy face), ": D" (allusion to the smiling face), ":(" (allusion to the sad face), of 90% of the posts, the agreement about the polarity of feeling attributed to the users was on average 95%. However, they also found that the emoticons which are most often used to express an emotional state of irritation or discomfort, ": /", for example, indicated a negative polarity for about 60% of the participants and neutral for about 20 %. These results suggest that there is not a single relationship between both the emoticon and the polarity of feeling and that the variation could be caused by the specific features of different users.

In [31] was extracted emotions from posts from Facebook users in northern Italy, including text and emojis. Through a Linguistic Inquiry and Word Count (LIWC) and correlation analysis of positive or negative valence, it was possible to recognize some indications of depression, stress and anxiety. In addition, the authors evaluated the behavior of groups by age group, as, for example, it was pointed out that groups of young people tend to express emotions more frequently in their social network posts.

Wegrzyn-Wolska *et al.* [16] also explored the relationship between emoticons and sentiment expressions on registered tweets. In doing so, the authors compared three pre-processing lexicon-based methods of emoticon-weight on the Twitter-aware tokenizer with a Basic Twitter Sentiment Analysis (TSA) of the fifty most widely used emoticons that employ a Naïve Bayes (NB). The authors described a group of specific emoticons that can indicate either positive or negative polarity, as well as the following feelings: happiness, surprise, playfulness, affection, acknowledgement, sadness, annoyance, distress, anger and indifference. Their results demonstrated that the use of the emoticon-weight lexicon was a means of upgrading the task of sentiment analysis. It also showed that an emoticon can control the sentiment expression of a tweet, by subduing the emotion of the verbal message. Thus, emoticons may not always belong exclusively to one category of polarity.

In [32], the authors describe a model that can identify some scenarios of blue feeling, e.g., sadness, loneliness and others depressed feelings. The authors describe the approach adopted to analyze users posts on social media networks (SMNs) by using natural language processing techniques, e.g. emotional labeling of the text and Emoticon-Based Text Annotation for Training Set. The proposed approach is evaluated through an experimental session over a dataset of Facebook posts. In order to quantify the performance of dynamic lexicon for the detection of negative sentences, the results of F1-measure obtained for the classes sadness, fear, anger, and disgust have been averaged. However, the values obtained for dynamic lexicon is 35.00 against 26.65 for MLP and 20.98 for Naive Bayes, which is a statistically significant difference.

Marengo *et al.* [33] explore the use of emoji and its relation to personality traits. For this, a Big Five personality assessment questionnaire and a 91-item survey are applied validating the degree of self-identification of the participants with the Apple Color Emoji. Results showed that only 36 emojis are significant in terms of personality traits, such as emotional stability, pleasantness and extroversion. However, the results allow to affirm that the use of emoji allows a free analysis of the language.

In [34] is presented a database of emojis and emoticons, collected from iOS, Android, Facebook and Emojipedia, built with the objective of evaluating several aspects, such as aesthetic aptness, familiarity, visual complexity, concreteness, excitement and meaning. For this, a research was conducted with participants, where each participant evaluated a set of 20 emojis / emoticons. Finally, the authors present quantitative and descriptive results of the norms obtained, as well as their correlations, examining all datasets.

In [35] solve the problem of noisy labels about the emotional meanings using words and emoticons together. For this, the authors constructed an emotional space as a representation matrix and projected emoticons and words into this emotional space through semantic composition. In addition, a new emotion-semantic-enhanced convolutional neural network (ECNN) model was created using a Multilayer Perceptron (MLP) as a way to improve performance. Furthermore, by projecting emoticons and words into an emoticon space, it was possible to identify subjectivity, polarity and emotion in microblog environments.

The Table 1 presents a summary of the related works highlighting the main approach, social network, character level used (emoji, emoticon or reaction) and the and the emotions assessed in the study. Through the related works, it is possible to perceive that some of them employ common technical approaches based on sentiment lexicon. Some of them combine lexical analysis with other techniques, such as [16] that it uses along with Naive Bayes and [14] with finite state machines. In relation to the emotions evaluated, most of the works evaluate only the valence of the feeling, that is, if it is neutral, positive or negative. [16], [26], [35] evaluate some emotions and mood disorders, but only [32] evaluates Ekman's basic universal emotions using a lexical sentiment analyzer.

In contrast to previous studies, the present study addresses the use of a specific set of emoticons called reactions. These reactions have been built by Facebook so that your Facebook users can react sentimentally to posts on the network. For this, through correlations and a clustering algorithm based on estimation and maximization, the study investigates how well these reactions could represent emotion in real life, evaluating the polarities, distribution between emotions and relating to the basic and universal emotions of Ekman [8], a form of non-virtual expression. Details of the methodology can be found in the next section.

III. MATERIAL AND METHODS

The data collection of this study involved the selection of popular news on Facebook, analysis of the reliability of the news by expert judges, a collection of data with Facebook users from a questionnaire elaborated with this news, and correspondence analysis between reactions and basic emotions. Each of the steps will be described below.

A. SELECTION OF NEWS

Three different researchers selected the news that could be initially used, by surveying the largest news sites posted on their respective Facebook pages, in accordance with the following criteria: 1) they had been posted in the last two days,

TABLE 1. Summary of the related work, including the main approach, social network (source) type of character used and the emotions evaluated in each study.

Study	Main Approach	Social Network	Character level	Emotions assessed
[23]	Sentiment lexicon	Twitter	Emoji	Valence
[26]	Probabilistic Language Model	Twitter	Emoji	Valence
[27]	MoodLens	Twitter	Emoticon	Valence, angry, disgust, joyful, sad
[28]	Sentiment lexicon	Twitter	Emoji	Valence
[29]	Sentiment lexicon	Twitter	Emoji	Valence
[30]	Sentiment lexicon	Twitter	Emoji	Valence
[14]	Sentiment lexicon and Finite State Machines(FSM)	Facebook	Emoji	Valence
[31]	Sentiment lexicon	Twitter	Emoji	Valence
[22]	Word2vec and Kmeans	Twitter	Emoji	Valence
[32]	Linguistic Inquiry and Word Count (LIWC)	Facebook	Emoji	Valence and Anger
[16]	Sentiment lexicon and Naive Bayes	Twitter	Emoji	Valence, happiness, surprise, sadness, anger and indifference
[33]	Sentiment lexicon	Facebook	Emoji	Happiness, anger, sadness, fear, disgust, surprise
[34]	Sentiment lexicon and finite state machine	Facebook	Emoticon	Valence
[35]	Correlation	Facebook and Emojipedia dataset	Emoticon	Valence
[36]	Multilayer Perceptron (MLP)	Twitter	Emoticon	Neutral, happy, sad, disgust

i.e. to ensure that they were current news; 2) they had more than 500 reactions from the readers, to show that they were news outlets with a wide circulation; 3) they must be free of bias and neutral, i.e. without any religious content, or mention of political and public figures; 4) Six stories were selected to express the six emotions that needed to be evaluated, with the total agreement of the selection group, which meant that a total of thirty-six news items were compiled. The posts describing the news in question should present an image and a phrase that drew attention to what was being portrayed. For example, the image of a burned-out car next to a police car is presented to illustrate the phrase "Carbonized body is found inside car in prime neighborhood of the city". The image of an industrial kitchen containing food on a table is used to illustrate the phrase "Procon finds overdue food in seven famous restaurants". And finally, the image of a child, a couple and another adult portrays the phrase "Marrow donation joins a man and the family of the baby he saved".

B. ANALYSIS OF CORRESPONDENCE BETWEEN NEWS AND BASIC EMOTIONS

The posts were assessed by a panel of seven expert judges so that a set of news items could be compiled that were suitably related to the six emotions proposed in the study by Paul Ekman [6], [8] for the following analysis. The judges were both professionals and post-graduate students in the field of psychology who are conducting research on how to investigate human emotions. For each news, the judges evaluate separately what was the perceived thrill to watch her. Of the 36 news items initially chosen by the researchers, 24 were selected as the most representative (4 news items related to each emotion), based on the following criteria: 1) a majority of the judges found the same emotion in one news item.; and 2) a majority of the participants found an emotion in the same news item. These criteria resulted in higher percentages of agreement among the judges. The 36 posts were initially presented so that it was possible to discard the less representative posts of each emotion. The choice of 24 posts was based on the estimated amount of at least three items (i.e., three posts) for each factor (i.e., each emotion). It is a consensus among researchers that each factor must present at least three items to support the veracity of the items in relation to the factor [36]. The questionnaire, in the present study, consisted of four items (i.e. four posts) for each emotion, and all the postings selected to compose the questionnaire presented moderate to excellent correspondence between the judges (>70%, [37]), according to criteria described above. The titles of the posts, grouped for each emotion, are shown in Table 2.

C. GENERAL DESCRIPTION OF THE QUESTIONNAIRE

The study used a questionnaire that was prepared with the aid of the Lime Survey tool. The instrument was based on the 24 selected postings as described above, and for each post three questions were asked to be answered by clicking on one of the answer alternatives: 1) What Facebook reaction would you give to the post? The answer could range between the six options of reactions in graphical form, among those of the emotions that the Facebook social network makes available; 2) How do you rate this post? The answer could be positive, negative or neutral; 3) Which emotion is most prevalent in this post? The answer could range from "I do not recognize it" to the six basic emotions: joy, sadness, fear, disgust, anger and surprise. In questions 1 and 2 only one answer alternative could be selected for each question. In the third question, the user could choose up to two predominant emotions.

TABLE 2. News selected according to judges' analysis. From left to right: the news number, the title in English, and the average concordance between the judges. The images, which were presented to the participants can be viewed in GitHub[1].

Emotion and posts	Judges' concordance (%)
Joy	
(4) Justice decides that parrot raised by the elderly can not be taken by Ibama	71,42%
(10) The world's first water park designed for people with special needs opens in the USA	85,71%
(21) 12 year old boy realizes dream of going to the movies	71,42%
(24) Boy with leukemia receives bone marrow transplant donated by younger brother	85,71%
Sadness	
(12) Carbonized body is found inside a car in the prime neighborhood of São Paulo	100%
(13) I hoped to hold my daughter and now there's nothing more. It is inhumane	85,70%
(26) Working with recycling in polluted air is unique alternative for Syrians	85,71%
(27) Boy loses balance and falls on the slab while bucked kite	71,42%
Anger	
(2) Globo anticipates report of stepmother Isabella Nardoni and promoter will recommend semi-open prison	71,42%
(7) After irritating with crying, stepfather kills with punches child of two years	57,14%
(23) Residents 'fish' in a hole to criticize street abandonment in the interior of SP	57,14%
(28) Woman attacks 12 year old girl after boyfriend gives on teenager	85,71%
Disgust	
(20) Procon finds overdue food at seven famous SP restaurants	42,85%
(30) Girl contracts worm that reached almost 3 meters after eating infected sashimi	28,58%
(16) Fan is beaten in a fight between fans in Curitiba	28,57%
(35) 6 out of 10 Brazilians consider applications as essential as eating	42,85%
Fear	
(15) Thieves surrender security guards and steal almost 400 guns from forum in the great SP	71,42%
(29) Man has killed a coworker because he thinks she would cause him to resign	71,42%
(31) Get rid of canker sores in an instant with this powerful home remedy	28,58%
(32) Horror films that debut in the next few years	57,14%
Surprise	
(33) Macabre: Child's mummy is found in church and hides secret	71,42%
(25) World's oldest gymnast still active at age 91	85,71%
(11) NASA discovers 10 new planets that can harbor life	57,14%
(5) Vatican investigates Brazilian Catholic organization for pact with Satan	100%

D. DATA COLLECTION WITH USERS

Users of the Facebook social network were invited to participate in the study by means of a formal invitation made available in the digital media, either personally or on the researchers' social network platform. Before the respondent could be included in the study, he/she had to: 1) be an adult (eighteen years or over); 2) be a user of the social network Facebook; and, 3) have answered the entire questionnaire. Interested participants were invited to respond to the questionnaire described in section III-C available on the laboratory website and disseminated on digital platforms. The instrument was made available to interested parties for a period of approximately three weeks. When they accessed the research web page, the participants were initially informed of the rationale, purpose, and implications of the study, and given an assurance of confidentiality through a Free and Informed Consent Form. If the participant consented by following the proper acceptance procedures, the questionnaire could be answered immediately. The user's IP address was checked and also there was storage of cookies to ensure only a single response was made by each person; the user could also stop and return to an earlier reply at any time.

[1]GitHub Link: https://github.com/ftgiuntini/Reactions-Study

At the end of the questionnaire, the participants were given final guidelines for making contact and thanked for taking part. The information submitted was automatically made available to the researchers and contained the raw data of each participant. The individual results were examined, and two questionnaires were excluded because they did not meet any of the inclusion criteria (both respondents were minors aged 14). Thus, one hundred and forty-seven questionnaires were analyzed. The average rate of agreement of users in relation to the predominant emotion can be checked in Table 3.

E. CORRESPONDENCE ANALYSIS BETWEEN REACTIONS, THE POLARITY OF FEELING, AND BASIC EMOTIONS

Considering that it is intended to verify the polarity of feelings and how well Ekman's six basic emotions can be represented by Facebook's Reactions, and starting from the assumptions: (i) that more than one emotion can occur at the same time before an event, such as observing a news post; (ii) that every human can have an interpretation of the news and the reaction, one has a complex problem of separation, taking into account that it is necessary to check how well each emotion can be signed by each class, which in this case are Facebook reactions; (iii) the non-normal distribution of the data collected and selected for final analysis as can be seen by histogram in Figure 2. Thereby, the simple

TABLE 3. Average rate of agreement among Facebook users participating in the survey. From left to right: the news number, the title in English, and the average concordance between the users.

Emotion and posts	Users' concordance (%)
Joy	
(4) Justice decides that parrot raised by the elderly can not be taken by Ibama	55,10%
(10) The world's first water park designed for people with special needs opens in the USA	97,96%
(21) 12 year old boy realizes dream of going to the movies	95,24%
(24) Boy with leukemia receives bone marrow transplant donated by younger brother	90,48%
Sadness	
(12) Carbonized body is found inside a car in the prime neighborhood of São Paulo	74,83%
(13) I hoped to hold my daughter and now there's nothing more. It is inhumane	85,71%
(26) Working with recycling in polluted air is unique alternative for Syrians	84,35%
(27) Boy loses balance and falls on the slab while bucked kite	78,23%
Anger	
(2) Globo anticipates report of stepmother Isabella Nardoni and promoter will recommend semi-open prison	63,27%
(7) After irritating with crying, stepfather kills with punches child of two years	80,95%
(23) Residents 'fish' in a hole to criticize street abandonment in the interior of SP	44,22%
(28) Woman attacks 12 year old girl after boyfriend gives on teenager	59,89%
Disgust	
(20) Procon finds overdue food at seven famous SP restaurants	57,82%
(30) Girl contracts worm that reached almost 3 meters after eating infected sashimi	78,91%
(16) Fan is beaten in a fight between fans in Curitiba	23,80%
(35) 6 out of 10 Brazilians consider applications as essential as eating	14,29%
Fear	
(15) Thieves surrender security guards and steal almost 400 guns from forum in the great SP	17,00%
(29) Man has killed a coworker because he thinks she would cause him to resign	14,97%
(31) Get rid of canker sores in an instant with this powerful home remedy	20,41%
(32) Horror films that debut in the next few years	7,48%
Surprise	
(33) Macabre: Child's mummy is found in church and hides secret	73,47%
(25) World's oldest gymnast still active at age 91	69,39%
(11) NASA discovers 10 new planets that can harbor life	70,09%
(5) Vatican investigates Brazilian Catholic organization for pact with Satan	51,02%

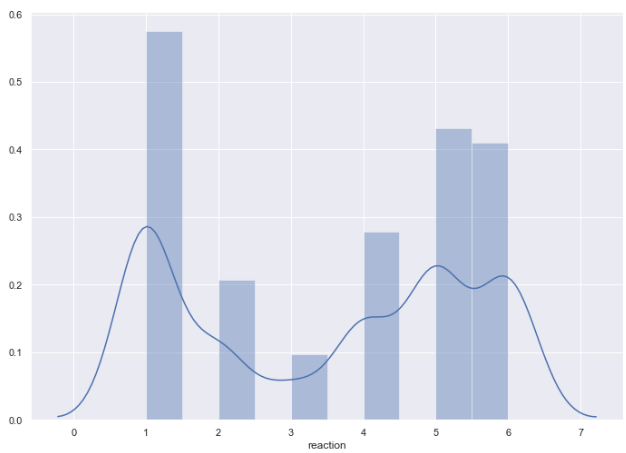

FIGURE 2. Histogram of the final dataset in which each instance contains: A reaction, the polarity and even two emotions chosen by the user.

Expectation-Maximization (EM) special dataset[2] was used with 3,528 instances (24 news vs 147 responses) to find a matching rate between Ekman's universal emotions and Facebook reactions, as well as to understand the users' feelings when they adopt this feature in the posts. Each instance contains a reaction (like, love, haha, wow, sad, angry), a polarity (positive, negative, neutral) and even two emotions (joy, sadness, anger, fear, disgust, surprise) or 'Not recognize'. The choice of the EM algorithm is based on previous assumptions and for being the most popular approach to solving non-convex problems, with good performance even with missing data.

The EM clustering algorithm basically assigns a probability distribution to each instance to indicate the degree of probability of belonging to one of the clusters [38]. Then, by means of a) a statistical model which generates a X set of observed data, b) a set of unobserved latent data or missing values Z, and c) a vector of unknown parameters Θ, along with a likelihood function $L(\Theta; X, Z) = p(X, Z \mid \Theta)L(\Theta; X, Z) = p(X, Z \mid \Theta)$, the maximum likelihood estimate (MLE) of the unknown parameters is determined by the marginal likelihood of the observed data.

$$\mathbb{L}(\Theta; X) = p(X \mid \Theta) = \sum_{Z} p(X, Z \mid \Theta) \tag{1}$$

For this reason, an initial model (Θ_θ) has been created with arbitrary parameters. The EM phase seeks to find the MLE of the marginal likelihood by iteratively taking the following two steps:

1) **Expectation step (E)**: In this step, the missing data are calculated on the basis of the observed data and current

[2]Available in https://github.com/ftgiuntini/Reactions-Study

estimates of the model parameters. Thus, the expected log value of the likelihood function is defined in terms of the conditional distribution of Z given X from the current estimate of the $\Theta^{(t)}$ parameters:

$$Q(\Theta \mid \Theta^{(t)} = E_{Z|X,\Theta^{(t)}}[\log L(\Theta; X, Z)] \tag{2}$$

2) :**Maximization step (M)**: The 94-likelihood is maximized by making an assumption that the missing data is the known maximization. Thus, the 95-maximization parameter is completed as follows:

$$\Theta(t+1) = arg\ max\ Q(\Theta \mid \Theta^{(t)}) \tag{3}$$

Finally, the algorithm continues by repeating the EM steps above until it reaches the local maximum. Thus, the cluster number was defined as the number of classes (reactions) and other parameters were initialized with the default values, such as the number of seeds equal to 100 and folds and k-means executions equal to 10; the algorithm continues by repeating the steps EM steps outlined above, until it reaches a local maximum.

IV. RESULTS

149 questionnaires were completed and 147 instruments that met the criteria were included in the final analysis. The data obtained were transferred to an MYSQL database so that they could be handled more easily. Responses were provided, mostly (85%), by young adults (18 to 35 years) of both sexes. Half of the participants stated that they had subscribed to Facebook for more than 6 years and used it for 2 - 5 hours a day (37%).

Figure 3 shows both the percentage of reaction and the valences assigned to different categories of emotion to the news. From an examination of the results of the reaction attribution, it can be seen that *joy news* received the highest attribution of either the reaction's "like" (42.6%) or "love" category (50.9%), with a strong negative correlation between them (Spearman, r = −0,88, p <0.001). The differences were statistically significant (Friedman, $\chi^2(5)$ = t = 536.15, p <0.001). Although no differences were observed between the reaction "like" and "love" (t = −0.250, p <1,000), the assignments to these reaction were significantly higher than those of other reactions [(love: Haha, t = 1.519, p <0.001; Wow, t = 1.417, p < 0.001; sad, t = 1.481; p < 0.001, angry; t = 1,500, p < 0.001); like: Haha, t = 1.269, p < 0.001; Wow, t = 1,167, p<0.001; sad, t = 1,231, p<0.001; and, angry, t = 1.250, p < 0.001)]. Emotionally sad news received mostly sad reaction (74.7%), and no participant attributed "love" to any item of news in this condition. The attribution of sad reaction was significantly higher than all the other responses [Friedman, $\chi^2(5)$ = t = 811.15, p < 0.00; like (t = −1.889, p < 0.001), love (t = −2.241, p < 0.001); Haha (t = −2.231, p < 0.001); Wow (t = −1.917, p < 0.001); and, angry (t = 2.167, p < 0.001)]. News angry received a strong attribution of reaction and angry (49.7%) was significantly higher than the others [Friedman, $\chi^2(5)$ = t = 288.15, p < 0.001; like, t = −1, 111, p < 0.001; love, t = −1.491, p<0.001; Haha,

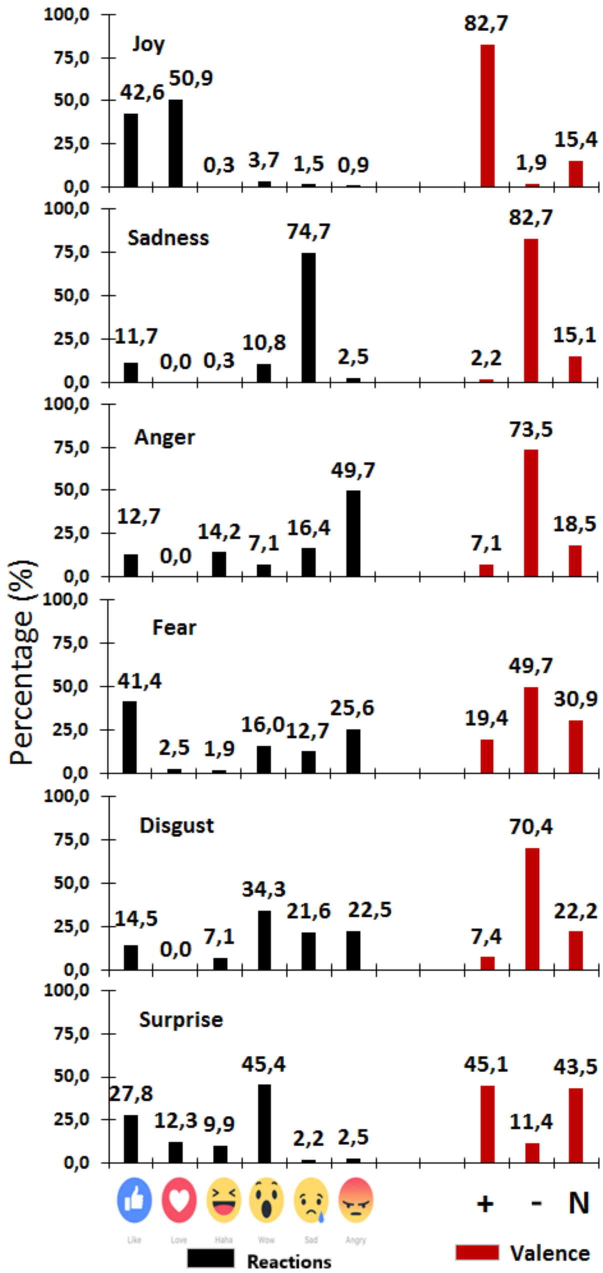

FIGURE 3. Percentage of reaction and valences attributions with regard to the emotion category of the news.

t = −1.065, p < 0.001; Wow, t = −1, 278, p<0.001; and, Sad, t = −1.000, p < 0.001)]. The News classified as fear received the reaction of like in 41.4% of the situations; this value was significantly higher than the other reaction [Friedman, $\chi^2(5)$ = t = 219,15, p<0.001; love (t = 1,167, p < 0.001); Haha (t = 1,185, p < 0.001); Wow, (t = 0,759, p < 0.001); sad (t = 0,861 p < 0.001); and angry (t = 0,472, p < 0.020)]. The attributions to disgust news was distributed between Wow (34.3%), angry (22.5%) and sad (21.6%); these reaction values were not statistically different (Wow versus sad: t = 0.352, p < 0.250; Wow vs Angry: t = 0.380, p < 0.147; and, Sad vs. Angry: t = −0.28, p < 1,000).

There was a significant difference when the Wow reaction was compared with all the other ones [Friedman, $\chi^2(5) = t =$ 144,30, $p < 0.001$; like, $t = -0.593$, $p < 0.001$; love, $t = -0.28$, $p < 0.001$; and, Haha, $t = -0.815$, $p < 0.001$]. Moreover, the differences were statistically representative when angry reaction was compared with both love ($t= -0,676$, $p<0.001$) and Haha ($t= -0,463$, $p<0,025$); and the sad one with either love ($t= -0,648$, $p < 0.001$) or Haha ($t= -0,435$, $p<0,046$). Surprise news received a significantly higher attribution in the reaction Wow (45.4%) [Friedman, $\chi^2(5) = t = 276{,}85$, $p < 0.001$; like ($t = -0.528$, $p < 0.005$), love ($t = -0.991$, $p < 0.001$; Haha ($t = -1.065$, $p < 0.001$); sad ($t = 1.296$, $p < 0.001$), and angry ($t = 1.287$, $p < 0.001$)]. Thus, the attribution of the reaction seems to have been relatively consistent with the way Elkman's emotion was attributed to the news, although it was not exclusive.

From a scrutiny of the valences attributed to the different categories of news (Figure 3), it is clear that *joy news* generally received a positive valence (82.7%), since it was significantly higher (Friedman, $\chi^2(2) = t = 364{,}52$, $p<0.001$) than the reactions - both negative (1.9%; $t=1{,}213$, $p<0.001$) and neutral (15.4%, $t = 1.009$, $p < 0.001$); the neutral assignment was also statistically higher than the negative one ($t = 0, -204$, $p < 0.029$). The reaction love had both a positive correlation with a positive valence (Spearman bivariate correlation, $r = 0.43$, $p < 0.001$) and a negative one with a neutral valence ($r = -0.40$, $p < 0.001$). However, the like reaction showed opposite results: a negative correlation with a positive valence ($r = -0.35$, $p < 0.001$) and a positive correlation with the neutral one (Spearman bivariate correlation $= 0.39$, $p < 0.001$). In the Sad news, the differences in valences were also representative (Friedman, $\chi^2(2) = t = 363.72$, $p < 0.001$), with the negative valency was significantly greater than the positive valence (2.2%; $t = -1.208$, $p < 0.001$) and the neutral (15.1%, $t = 1.014$, $p < 0.001$); the neutral valence was statistically higher than the positive one ($t = -0.194$, $p<0.040$). In the category of anger, the valences were also significantly different (Friedman, $\chi^2(2) = t = 240.07$, $p <0.001$). The negative valence was significantly higher than the positive one (7.1%, $t = -0.981$, $p < 0.001$) and neutral (18.5%, $t = 0.824$, $p < 0.001$); the neutral and positive valences did not show significant differences ($t = -0.157$, $p < 0.135$). With regard to the news fear, it can be seen that they received a higher negative rating (49.7%, Friedman, $\chi^2(2) = t = 45.352$, $p < 0.00$). The negative valence was significantly higher than both the positive (19.4%, $t = -0.454$, $p < 0.001$) and the neutral (30.9%, $t = 0.282$, $p < 0.001$); the neutral and positive values were not statistically different ($t = -0.171$, $p < 0.088$). The news with disgusting emotion received a mostly negative valuation (70.4%, Friedman, χ^2 $(2) = t = 210.67$, $p < 0.001$); this assignment was higher than either the positive valence ($t = -0.944$, $p < 0.001$) or the neutral ones ($t = 0.722$, $p <0.001$). Here it is also apparent that the neutral valence was appreciably greater than the positive valence ($t = -0.222$, $p < 0.014$). Finally, in the Surprise News, we observed a close distribution between the positive (45.1%) and neutral (43.5%) valences, with no significant difference between either of them ($t = 0.023$, $p < 1{,}000$); significant values were observed [Friedman, $\chi^2(2) = t = 70{,}13$, $p<0.001$] when the valences were compared - either positive versus negative ($t = 0.505$, $p < 0.001$) or neutral vs negative ($t = -0.481$, $p < 0.0011$).

The cluster number was defined as the number of classes (reactions) and other parameters were used to specify the default values, such as the number of seeds equal to 100 and folds and k-means executions equal to 10. For this reason, the distribution of basic emotions is shown in accordance with the clusters in Table 4.

By means of a class evaluation for clusters in the training data, we obtained the assignment of each reaction to the clusters shown in Table 5. Although there was a high recognition rate of basic emotions and a Log likelihood was obtained equal to 4.96, the cross-validation analysis observed in Table 2 shows that some reactions may belong to more than one cluster; that is, it may suggest that there is more than one emotion. As a result, it was pointed out that the maximum aggregation value that the reaction can offer an emotion is up to 56.6%, which is the hit rate obtained by employing the

TABLE 4. Distribution of Emotions in Clusters by taking account of Facebook reactions.

Attribute	Clusters					
	0	**1**	**2**	**3**	**4**	**5**
Distribution	(0.14)	(0.16)	(0.28)	(0.07)	(0.2)	(0.15)
Joy						
mean	0.0017	0	0.0311	0.0054	0.9876	0.0398
std. dev.	0.0257	0.4101	0.1736	0.073	0.1109	0.1955
Sadness						
mean	0.0604	0	0.8725	0.0591	0	0.1053
std. dev.	0.2383	0.445	0.3336	0.2359	0.445	0.3069
Anger						
mean	0.0125	0	0.3494	0.1644	0.0176	0.6284
std. dev.	0.1109	0.0015	0.4768	0.3706	0.1315	0.4832
Disgust						
mean	0	0.0719	0	0.2055	0.0011	0.6262
std. dev.	0.0016	0.2584	0.3246	0.4041	0.012	0.4838
Fear						
mean	0	0.1113	0.1067	0.999	0.0087	0
std. dev.	0.3207	0.3145	0.3088	0.0321	0.093	0.3207
Surprise						
mean	0	1	0.0455	0.0017	0.2357	0.0831
std. dev.	0.4247	0.4247	0.2085	0.0263	0.4244	0.276
Not Recognize						
mean	0.9353	0.0274	0	0.0041	0.007	0
std. dev.	0.2461	0.1632	0.0062	0.0639	0.0832	0.0013

TABLE 5. A evaluation of the classes of clusters in the training data.

0	1	2	3	4	5	Class assigned to cluster
376	219	35	52	292	62	Like
5	9	0	0	350	1	Love
51	55	7	3	34	23	Haha
17	269	26	62	57	74	Wow
14	77	560	65	3	52	Sad
19	22	156	62	0	467	Angry

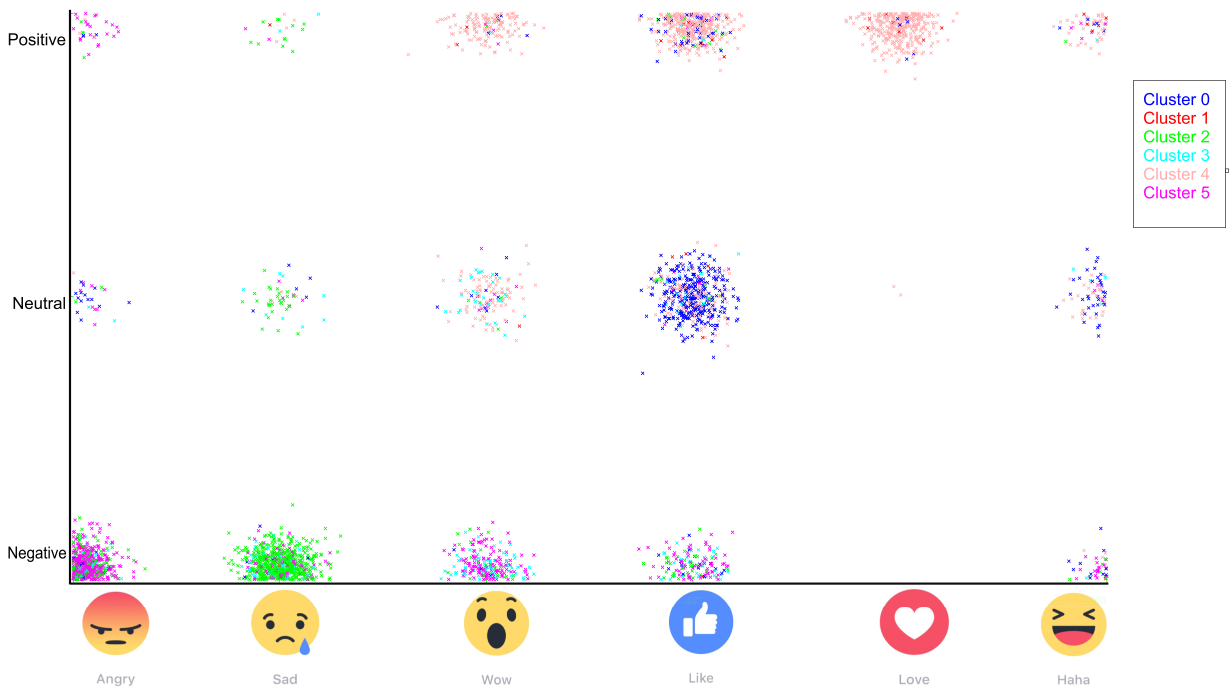

FIGURE 4. **Distribution of the clusters considering the class reactions and the polarity of the emotions.**

cross-validation system. It should be noted that the reaction "Like" is the one with the fewest representations of both the emotion and polarity of the feeling. In general, it can indicate neutrality and positivity, but despite this, it also appears to be negative.

In cluster 0, a group signed mostly by the like reaction, it is possible to perceive that the respondents do not recognize any emotion (Not recognize) with a rate of 93%, that is, indicating neutrality. The "joy" emotion is mainly represented by Cluster 4 and the reaction "Love" with a rate of 98%, which indicates an extremely positive polarity. However, the reaction "Haha" can represent a set of emotions, since it is distributed in several clusters and the number of instances in which it appears raises serious doubts about the reliability of this emotion. It may indicate a small degree of surprise (Cluster 1) and joy (Cluster 4), but it also appears in "Not Recognize". Meanwhile, the "Wow" reaction indicates a 100% surprise rate, and this surprise may be positive, negative or be even close to the neutral axis.

When Table 5 was examined more closely, it was found that the "Sad" reaction was the most expressive of the responses, since it represented an 87% rate of sadness and negative polarity. Moreover, the "Angry" reaction also received a high number of responses and its index could represent 62% of the two emotions at the time, with disgust and anger. With regard to the emotion of fear, it does not seem to have a reaction that represents it very well. This is evident from the fact that although it obtained a 99% index in Cluster 3, almost all the reactions participated in this cluster, except the reaction "Love".

Finally, with regard to the polarity distribution between positive, neutral and negative, it can be seen in Figure 4, that the division of the clusters was clear, and that the reactions represent the feelings in question. The emoticon clusters related to "Love" are almost entirely designated as positive polarity. On the other hand, "angry" and "sad" had the most significant concentration of clusters in the negative polarity. The emoticon "like" had clusters distributed in all the polarities.

This suggests that there has been a great advance in the representation of emotion in the area of non-textual information. With regard to Facebook reactions and other studies in the literature, Facebook reactions can add much more information about the emotions and feelings of the user, which was pointed out earlier with regard to the use of emoticons.

V. DISCUSSION

The fact that there is scientific evidence of a correlation between facial and body expressions and certain emotions is now universally recognized and has been widely documented in the literature [8], [39]–[42]. However, there have been few attempts to carry out scientific experiments to investigate this correspondence in the virtual environment - that is to correlate emoticons, sentiment identification and its polarity. The universal expressions of emotions are crucial ways of showing feelings [8]; as a result, it is possible to maintain that in virtual environments some of these functions the use of reactions. This could be an important development in the area of sentiment analysis. The use of indicators and emoticons for universal emotions should enable methods of emotional analysis to be employed with minimum dependence on verbal semantics. The sample of news items selected for the investigation was relatively complex given the fact that multidimensional features were used to express the information (which usually involved showing pictures and words), rather than only relying on facial information. However, the results showed a consistent attribution, particularly with regard to both emotion and valence, when using different news items; moreover, the division of the clusters was very successful, and the reactions represent the feelings in question very well. This could be an important step in carrying out scientific investigations that can make valid generalizations about emotions, ranging from real to virtual environments, as well as conducting studies of how emotion representation can take place in virtual environments with non-textual information.

Jibril and Abdullah [21] point out that the intensification of virtual interactions and expression of emotions through social media is a social phenomenon. This phenomenon may be related to the data found in the present study, as suggested by the time of use of the social network: 51% of the participants use it for 2 to 8 hours a day.

In virtual interactions, emoticons have become the most widely adopted means of expressing emotions [15]. A number of recent studies have been concerned with analyzing them [15]–[18], with the aim of **a)** correlating their use when tackling mental health problems; **b)** assessing reactions to stressful events; **c)** investigating preferences for brands or policy choices; and **d)** conducting several other opinion polls [14], [19], [20]. The Facebook social network provides particular emoticons called reactions. This new feature can provide us with clues on how to re-establish communication when it is lost in virtual technology, i.e., non-verbal clues [14]. It can also enable the kind of emotions that a posting arouses in your reader to be identified. It should be noted that owing to the successful division and distribution of the groups, the emotions were well represented. These distribution data in the attribution of emotions and polarity indicate that there might be a relationship between the emotions felt and the reactions expressed in the virtual environment. This can be illustrated by the following examples: **(1)** as expected, when the participants classified news as ''neutral'' category, most of them did not recognize any predominant emotional charge in its content (''I do not recognize it'' in 74% of the sample); **(2)** some emotions that in natural environments are not socially desirable or enjoyable, are not expressed with a high degree of frequency in virtual environments: the emotional content of the news was classified as disgust 7% of the times and fear 7% of the times.

When some authors investigated the polarity (negative, positive or neutral) of emoticons [17], they found that emotional states of irritation or discomfort were more closely associated with emoticons '':/ '', 60% of participants regarded them as negative; in the present study the ''sad'' reaction was also closely related (73% of participants) to a negative polarity/classification. Furthermore, in 45% of cases, the ''sad'' reaction could be correlated with the ''sadness'' emotion. Thus, it was possible to correlate not only reactions and emotions but also their polarities (neutral, positive and negative).

The ''like'' reaction can be regarded as a useful phenomenon; in the score for general news (34%) of the items were predominant among the seven choices of possible reactions. (24%), I do not recognize (22%), happiness (16%), I do not recognize (22%), sadness (18%), fear (11%), disgust (10%), anger (17%), as well as positive (29%), negative (34%) and neutral (37%) feelings. Moreover, if the participants did not recognize any emotion in the news, the ''like'' reaction was used 64% of the time; which corroborates the broad representativeness of this reaction.

Although the researchers selected the four most representative news stories for each emotion, by following the selection criteria for standardized news (i.e. news items that were circulating in the most representative sites of the news published via Facebook, within the two-day selection period, with at least five hundred reactions that had free and neutral content and accessible language), it was difficult to select news items with a high emotional load of disgust and sadness. This implies there is a trend that is of little value for the social network of Facebook - the linking of information with strong connotations of disgust or fear; or perhaps it suggests that fear and disgust are not socially important to their users.

Some authors have investigated whether there are trends in the use of emoticons and their degree of frequency, by searching for relationships between different features of the users (such as gender and personality) [15]. However, the results suggest that there is a need to carry out additional studies in the area to obtain a more accurate assessment of the influence of user features on the frequency and type of emoticons posted on the Facebook public feeds. By keeping the same variable with regard to ''frequency and type of emoticons (reactions, in the present study)'', and cross-checking the variable ''evaluation of news with a particular emotional load (anger, disgust, fear, joy, sadness and surprise)'', it was possible to establish a relationship between the use of reactions and the corresponding emotion generated by the news. News that was considered to be sad, for example (i.e. that was selected and evaluated as sad by the researchers, judges and participants) generally showed ''sad'' reactions (87%).

In view of the deepening immersion of individuals in virtual environments and the importance of the real representativeness of their emotional content when making use of the vast amount of abundant data generated, it is worth investigating factors that interrelate their personal traits (mental health, emotional reactions, preferences for brands, political inclinations, and information from opinion polls) and the way they have been expressed virtually (i.e. with emoticons), through data collected in virtual environments.

VI. CONCLUSION

This study has sought to show how reactions are distributed in the classification of polarity (positive, negative and neutral), and to examine whether they are related to the description of the basic emotions set out by Paul Ekman. This is a way of recognizing if what the user expresses in the virtual environment is something that can represent what he is actually feeling. Other studies may have investigated this factor, but only through establishing a correlation between the reactions posted in virtual environments and the textual analysis by means of **a)** finite state machines **b)** the Naive Bayes classification algorithm, and **c)** classifying the polarity of emotion. Although these methods are widely accepted in the field, they may still fail to recognize the user's emotion, since emoticons (especially those used with less frequency) and textual content may have ambivalent meanings. The way of expressing feelings in a virtual environment and their degree of frequency are also linked to sociodemographic features, and may be influenced by the textual content or the reactions already posted by other users in the public news feed.

This study was carried out in an analogous environment that is free from the influences of the responses of other users, to find out if in fact the chosen reactions were related to the expression of the universal emotions, on the basis of the attribution given by the user himself.

This study provided data that can assist in clarifying whether or not the reactions posted on the public Facebook feeds can be really reliable. Given the fact that emoticons are often used for the expression of feelings in a virtual environment, and that the use of the virtual environment is currently the predominant means of communication, there have been an increasing number of analyses on whether or not reactions are valid descriptions of emotion expression and this has encouraged new studies in the field. Analogous environments need to be more fully analyzed, as well as the correlation between the reactions used in the virtual environment with the expressions of universal emotions.

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