Article
Journal of Social Researches
June 2019 Vol.5 No.15 1-13

Index of suicide risk in Mexico using Twitter

Índice de riesgo al suicidio en México utilizando Twitter

RODRÍGUEZ-ESPARZA, Luz Judith[1]*†, BARRAZA-BARRAZA, Diana[2], SALAZAR-IBARRA, Jesús[3] y VARGAS-PASAYE, Rafael Gerardo[4]

[1]*Universidad Autónoma Chapingo. Forest Science Division. Km 38.5, Carretera México-Texcoco, Texcoco, Estado de México, CP 56230, Apartado Postal No. 37. Mexico.*
[2]*Universidad Juárez del Estado de Durango, Faculty of Exact Sciences. Av. Veterinaria 210, Valle del Sur, CP 34120 Durango, Dgo. Mexico.*
[3,4]*PhD student at Universidad Iberoamericana León. Blvrd Jorge Vértiz Campero 1640, Fracciones Cañada de Alfaro, CP 37238 León, Gto. México*

ID 1st Author: *Luz Judith, Rodríguez-Esparza* / **ORC ID:** 0000-0003-2241-1102, **CVU CONACYT ID:** 173460

ID 1st Coauthor: *Diana, Barraza-Barraza* / **ORC ID:** 0000-0002-6041-4657, **CVU CONACYT ID:** 372480

ID 2nd Coauthor: *Jesús, Salazar-Ibarra* / **CVU CONACYT ID:** 214090

ID 3th Coauthor: *Rafael Gerardo, Vargas-Pasaye* / **CVU CONACYT ID:** 1015314

DOI: 10.35429/JSR.2019.15.5.1.13 Received March 10, 2019; Accepted June 20, 2019

Abstract

Objectives: To identify early suicide risk signs on depressive subjects, so that specialized care can be provided. Various studies have focused on studying expressions on social networks, where users pour their emotions, to determine if they show signs of depression or not. However, they have neglected the quantification of the risk of committing suicide. Therefore, this article proposes a new index for identifying suicide risk in Mexico. Methodology: The proposal index is constructed through opinion mining using Twitter and the Analytic Hierarchy Process. Contribution: Using R statistical package, a study is presented considering real data, making a classification of people according to the obtained index and using information from psychologists. The proposed methodology represents an innovative prevention alternative for suicide.

Suicide, Analytic Hierarchy Process, Twitter

Resumen

Objetivos: Identificar de manera temprana indicios de riesgo de cometer suicidio por personas depresivas, de forma que se les pueda proporcionar la atención especializada pertinente. Diversos estudios se han centrado en estudiar las expresiones en redes sociales, donde los usuarios vierten sus emociones, para determinar si muestran indicios de depresión o no. Sin embargo, han dejado de lado la cuantificación del riesgo de cometer suicidio. Por ello, este artículo propone un nuevo índice para identificar el riesgo al suicidio en México. Metodología: La propuesta de este índice se construye a través de la minería de opinión utilizando Twitter y el Proceso Jerárquico Analítico. Contribución: Utilizando el paquete estadístico R, se presenta un estudio considerando datos reales realizando una clasificación de las personas de acuerdo al índice obtenido y utilizando información proporcionada por psicólogos. La metodología propuesta representa una alternativa innovadora de prevención al suicidio de las personas.

Suicidio, Proceso Jerárquico Analítico, Twitter

Citation: RODRÍGUEZ-ESPARZA, Luz Judith, BARRAZA-BARRAZA, Diana, SALAZAR-IBARRA, Jesús y VARGAS-PASAYE, Rafael Gerardo. Index of Suicide Risk in Mexico using Twitter. Journal of Social Researches. 2019, 5-15: 1-13

* Correspondence to Author (email: judithr19@gmail.com)
† Researcher contributing first author.

June 2019 Vol.5 No.15 1-13

Introduction

Suicide in Mexico has increased considerably in recent decades. Analyzing suicide risk represents an indispensable task due to the psychological burden that it entails. According to the National Institute of Statistics and Geography (INEGI), in 2016 there were 6,291 suicides, representing a rate of 5.1 suicides per 100,000 inhabitants. Chihuahua and Yucatán doubled the national rate with 11.4 and 10.2 suicides per 100,000 inhabitants respectively. In addition, eight out of 10 suicides during 2016 were committed by men, that is 5,116 of 6,291 suicides (INEGI, 2018).

The World Health Organization (WHO) has defined suicide as the deliberate act of taking one's own life (Jiménez-Ornelas & Cardiel-Téllez, 2013); this fact is considered serious and harmful both for the individual who commits it, as well as their context, because of the destructive intention in it.

WHO considers suicide as a serious public health problem and points out that the effects on families, friends and society are complex and lingers after the loss (WHO, 2018). Among the reasons that cause it, various biological, psychological, social, environmental and cultural factors are indicated.

In psychological terms, the suicidal behavior is composed of emotional and cognitive factors that lead the individual to seek in death a solution to the frustrations, sufferings, anger or fears that overwhelm them (Jiménez-Ornelas & Cardiel-Téllez, 2013). These authors, in turn, show the suicide tendency in Mexico 1990-2011 considering socio-demographic factors.

Within an emotion there are complex physiological, social and psychological aspects. In order to explain this in a graphic way, the American psychologist Robert Plutchik (1927-2006) developed an evolutionary theory about emotions. He proposed that both animals and humans have evolved their emotions to adapt our organism to the environment.

The eight basic emotions proposed by Plutchik (2001) are: Joy, Trust, Fear, Surprise, Sadness, Disgust, Anger and Anticipation.

In his model, each emotion has its opposite, for example, the opposite of Sadness is Joy and the opposite of Trust is Disgust.

An aspect highlighted by Plutchik (2001) is the intensification of emotions; for example, boredom when intensified becomes anger. And, if left unchecked, emotions become feelings that can result in mental health problems.

In this sense, the analysis of feelings or opinion mining is a novel area of research which arises in response to the desire to know the opinions and trends that people follow in social media, blogs or websites dedicated to various activities. Bing Liu (2012, p. 7) defines the analysis of feelings as: "The analysis of feelings, also called opinion mining, is the field of study that analyzes opinions, feelings, assessments, attitudes and emotions of people towards entities and their attributes expressed in written text."

The purpose of the analysis of this information is diverse and recent research indicates that it can be applied in areas such as finance, economics, politics, market research, among others.

On the context of text mining, the characteristics of interest for this work are the words that identify and differentiate the emotions expressed in a text, in order to quantify the suicide risk by the person writing said text. To generate this quantification, this paper presents the technique of the Analytical Hierarchical Process (AHP) as a tool to hierarchically classify the eight basic emotions expressed in social media publications, and then use this hierarchy and generate a suicide risk index of the person who writes the analyzed texts. Since suicide is a serious Public Health problem, its timely detection and prevention are very important for society.

This article represents an instrument aimed at both social and professional groups, particularly relevant in suicide prevention. It also represents a link in a long and diversified chain that includes a wide range of people and sectors, including health professionals, educators, social organizations, governments, legislators, communicators, families and communities.

ISSN 2414-4835

The rest of this paper is organized as follows. Section 2 shows the background of the AHP, as well as the definitions of emotions. Section 3 presents the proposed methodology for the construction of the suicide risk index. An application of the proposed methodology is presented in Section 4, followed by Section 5 with the annexes. Finally, Section 6 provides the closing comments on this article.

1. Background

Below is some main background on two topics which will be of importance in the proposed methodology for calculating the suicide risk index: Emotions and the AHP.

1.1. Basic emotions and suicide

According to Plutchik (2001), there are eight basic emotions, with their corresponding opposite emotion, which are also related to the human being's series of adaptive behaviors. The eight basic emotions that Plutchik (2001) enumerates in his roulette are joy, trust, fear, surprise, sadness, disgust, anger and anticipation; they are basic emotions that manifest with a purpose or with a certain behavior. Thus, the emotional response of joy comes through a reproductive stimulus, bonding and search for a partner. Trust is caused by membership in a group, sharing with others and the support of the group. Fear responds to an intimidating stimulus, given a threat, as a protective shield that prepares us for defense or flight. Surprise is a response of the individual to novelty, which prepares them to sharpen attention, to be alert and properly oriented. Sadness is a response to a loss that initiates a process of reintegration and assimilation of harmful events, seeking help and comfort. The stimulus of disgust is the rejection of negative influences and unpleasant things that drives us to move away. Anger responds to the presence of an obstacle, which gives us strength to attack and destroy. And anticipation is caused by the stimulus to analyze and discover new territories, as well as the search for answers (Brujita, 2016).

On the other hand, suicide can be understood from different perspectives: from the religious, philosophical and sociological perspective, to the psychological and biological perspective (Hernández-Urbay, D., n.d.).

In the context of this study, we will address mainly the psychological approach. According to the classification of suicidal behavior, this article considers suicidal ideas and parasuicide or attempted suicide. Moreover, it is worth mentioning that biological factors, family, situations and substance abuse are the main agents of suicide, and as such, are beyond the scope of this study, which is limited to the analysis of texts in social media.

Many warning signs of possible suicidal emotions are also symptoms of depression and stress. Observing the following behaviors helps identify people who may be at risk of suicide: changes in eating and sleeping habits; loss of interest in usual activities; withdrawal from friends and family members; manifestations of contained emotions and estrangement or flight; abuse of alcohol and drugs; neglect of personal appearance; unnecessary risk situations; concern about death; increased physical discomfort, frequently associated with emotional conflicts, such as stomach aches, headaches and fatigue; loss of interest in school or school work; feelings of boredom; difficulty to focus; desire to die; lack of response to praise; statements of plans or attempts to commit suicide, including the following behaviors: verbalizing: "I want to kill myself" or "I will commit suicide"; giving verbal cues such as: "I won't be a problem for much longer" or "If something happens to me, I want you to know that..."; giving away their favorite items; throwing away important belongings; suddenly becoming cheerful after a period of depression; can express strange thoughts and write one or several suicide notes (Stanford Children's Health, n.d.) Suicide threats mean despair and a request for help. Feelings, thoughts, behaviors or suicide plans should always be taken seriously.

What is sadness? What is anger? What is fear? Are they just words or is there something else? In principle, sadness, anger, and fear are emotions. In general, emotions are usually considered to correspond to natural bodily experiences that are then expressed through language, and that language, in turn, is usually described as irrational and subjective. That is, we first feel in the body what later comes out of our mouths in the form of a discourse that somewhat opposes reason.

Emotions are also said to be originated in the unconscious and not in the will, which makes them more spontaneous than artificial, i.e., more “felt” than “thought.” Sometimes, they are mixed with behaviors considered rational, or the existential status of which belongs to the order of the non-emotional, and, recently, it is affirmed that they are not exclusive features of the interiority of people, but that they are social constructions of fundamentally discursive nature. 1) The construction of emotions has been neglected and 2) no attention has been paid to the very nature of the meaning of an emotion. Sometimes simple classifications have been proposed, for example, active emotions and passive emotions, or uncontrollable emotions subsidiary of the individual which unfold in the world outside of any regulation (Belli, S. & Íñiguez-Rueda, L., 2008.)

Emotions are psychophysiological reactions of people to situations relevant from an adaptive point of view, such as those that involve danger, threat, harm, loss, success, novelty, etc. These reactions are universal, quite independent of culture, and produce changes in the emotional experience (cognitive-subjective dimension), in the physiological activation (physiological-adaptive dimension) and in the expressive behavior (behavioral-expressive dimension). In addition, from a psychological point of view, emotions such as joy, fear, anxiety or anger are basic emotions which occur in all individuals of most diverse cultures, they have a considerable biological substrate, they are essentially pleasant or unpleasant, activate us and form part of the communication process with others and, in turn, they can act as powerful motives for behavior (Cano-Vindel, A. & Miguel-Tobal, J. J., 2001.)

Among the emotions, we can distinguish at least two groups: the positive and the negative. Fear-anxiety, anger, sadness-depression and disgust are basic emotional reactions that are characterized by an unpleasant or negative affective experience and high physiological activation. The first three are the most studied emotions in relation to health-disease processes. These reactions have a preparatory function so that people can give an adequate response to the demands of the environment, and thus they are considered eminently adaptive responses for the individual.

However, sometimes we find that some of them can become pathological in some individuals, in certain situations, due to a mismatch in frequency, intensity, context adaptation, etc. When such a mismatch occurs and is maintained for certain time, a health disorder can occur, both mental (anxiety disorder, major depression, pathological anger, etc.) and physical (cardiovascular, rheumatological, immunological disorders, etc.) (Piqueras- Rodríguez, J. A., Ramos-Linares, V., Martínez-González, A. E., Oblitas-Guadalupe, L.A., 2009.)

It is a fact that suicide is a process which begins with small manifestations in the subject’s behavior that denote a desire for self-destruction (González-Ganzábal, F., 2016.) These thoughts increase within the mind of the individual until the act is perpetrated. Suicidal ideas are constituted as a series of intrusive and repetitive thoughts that the subject presents regarding how to cause their own death, how to do it, what objects and/or methods to use and under which circumstances (González-Ganzábal, F., 2016.)

1.2. Emotion Detection in Social Media

The detection of mental problems through social media has taken relevance in recent years in response to the importance they have acquired in the lives of human beings, as shown by Guntuku, Yaden, Kern, Ungar and Eichstaedt (2017.) As Twitter is a more open social media than Facebook, several studies have focused on the study of the texts published in it. Nadeem (2016) used classification techniques such as decision trees, support vector machines (SVM), logistic regression and naïve Bayes for the analysis of texts shared by users over time.

Jamil, Inkpen, Buddhitha and White (2017) developed a methodology for the detection of depression in Twitter users, at tweet level. With this analysis, the levels of accuracy were biased by the disproportionality between the tweets with depressive content and those that did not present it, so they opted for an analysis at user level, considering the percentage of depressive tweets, thus improving the classification of depressed users. These classifications were carried out through SVM.

ISSN 2414-4835

Working also with Twitter, Orabi, Buddhitha, Orabi, and Inkpen (2018) developed models based on neural networks as classification techniques with high levels of accuracy, determining whether a user shows signs of depression.

Following the study of social media trend, Reece and Danforth (2017) focused on the analysis of photos uploaded to Instagram to detect signs of depression in users. Through Bayesian logistic regression models and a random forest-based classifier, the authors found that it is possible to identify depressive users through the photographs they share, being able to detect signs of depression even before the users are diagnosed with depressive symptoms by a mental health specialist.

So far, efforts in social media have been aimed at detecting signs of depression, without going into the study of suicide risk in users of these networks. It is relevant to note the central role that machine learning techniques, together with statistical classification techniques, play in the development of methodologies for the detection of symptoms of mental illness in social media users.

Thus, this paper will analyze the suicide risk through text analysis of publications made on the social media Twitter, considering the eight basic emotions presented previously (Plutchik, 201), ranking those emotions through AHP, a tool which has been rather useful in the areas of Mathematics and Psychology.

1.3. Analytical Hierarchical Process

Asdalifah Talibe, Aaturrawiah Ali Omar and Tong Sin Bei (2014) determined the most common criteria for depression among students of five science schools at Malaysia Sabah University by using the Analytical Hierarchical Process (AHP). Based on that article, we propose to use this process to study the suicide risk in Mexico through Twitter publications.

The AHP, introduced by Thomas Saaty in 1980 (Saaty, 1980), is an effective tool for making complex decisions, and can help the decision maker set priorities and find the best solution by reducing complex decisions to a series of pairwise comparisons. The AHP helps to capture both subjective and objective aspects of a decision.

Operationally, it helps build indexes, reducing complexity to a simple hierarchical scheme. The process requires that the decision maker provides subjective evaluations regarding the relative importance of each of the criteria, and then specify their preference with respect to each of the decision alternatives and for each criterion (Saaty, 2008.)

The AHP generates a weight for each evaluation criterion according to the decision of the maker, the specialist. Them, pair comparisons of the criteria are made. The higher the weight, the more important the corresponding criteria will be.

The objective of the deliberation is to express, in quantitative terms, the importance of the different elements, even though it is common to assign weight to the criteria, the specification of these is an issue in which there is no method generally accepted for its determination, considering this process as an aspect that can create controversies about the allocation of said weight.

2. Methodology

In this work we will use the AHP by making a comparison in pairs of the eight basic emotions, which starts from a square matrix in which the number of rows and columns is defined by the number of criteria to be pondered, that is, 8 by 8.

This establishes a comparison matrix between pairs of criteria, comparing the importance of each one of them with the others. Subsequently, the main eigenvector is set, which establishes the weight which in turn provides a quantitative measure of the consistency of value judgments between pairs of factors (Saaty, 1980).

The measurement scale considers the following score:

1- Equally important.
3- Slightly more important.
5- Notably more important.
7- Demonstrably more important.
9- Absolutely more important.

Let **A** be the comparison matrix, then **A** is of 8x8 dimension since there are 8 evaluation criteria considered.

Each a_{jk} entry in the matrix **A** represents the importance of the j-th criterion relative to the k-th criterion. If $a_{jk} > 1$, then the j-th criterion is more important than the k-th criterion, while if $a_{jk} < 1$, then the j-th criterion is less important than the k-th criterion. If two criteria are equally important, then the a_{jk} entry is 1. The a_{jk} and a_{kj} entries satisfy the $a_{jk}a_{kj} = 1$ condition. Obviously, $a_{jj} = 1$ for every j. The relative importance between two criteria is measured according to the numerical scale from 1 to 9 shown above.

Matrix A can be seen as follows:

	Joy	Trust	Fear	Surprise	Sadness	Disgust	Anger	Anticipation
Joy	1	a_{12}	a_{13}	a_{14}	a_{15}	a_{16}	a_{17}	a_{18}
Trust	$1/a_{12}$	1	a_{23}	a_{24}	a_{25}	a_{26}	a_{27}	a_{28}
Fear	$1/a_{13}$	$1/a_{23}$	1	a_{34}	a_{35}	a_{36}	a_{37}	a_{38}
Surprise	$1/a_{14}$	$1/a_{24}$	$1/a_{34}$	1	a_{45}	a_{46}	a_{47}	a_{48}
Sadness	$1/a_{15}$	$1/a_{25}$	$1/a_{35}$	$1/a_{45}$	1	a_{56}	a_{57}	a_{58}
Disgust	$1/a_{16}$	$1/a_{26}$	$1/a_{36}$	$1/a_{46}$	$1/a_{56}$	1	a_{67}	a_{68}
Anger	$1/a_{17}$	$1/a_{27}$	$1/a_{37}$	$1/a_{47}$	$1/a_{57}$	$1/a_{67}$	1	a_{78}
Anticipation	$1/a_{18}$	$1/a_{28}$	$1/a_{38}$	$1/a_{48}$	$1/a_{58}$	$1/a_{68}$	$1/a_{78}$	1

Once the comparison matrix is defined, it is normalized by columns and averaged by rows to obtain the vector of weight per emotion, also known as the main eigenvector (Saaty, 2003), which is composed of the weight obtained from each emotion. Let us denote this weight as w_i, $i = 1, 2, \ldots, 8$.

The next stage is the prioritization of the criteria or emotions, and consists in ordering the values of the weight w_i from least to greatest, each emotion obtaining a value J_i, $i = 1, 2, \ldots, 8$.

For the identification of emotions, (within tweets, in our case) we use the NRC-Word-Emotion Association Lexicon which consists of a list of words and their associations to the eight basic emotions, as well as to two feelings (positive and negative) (Saif & Turney, 2013.)

The annotations are made manually considering the tweets, resulting in the number of words (N_i, $i = 1, 2, ..., 8$) in each of the emotions, calculating as well the proportion of words in each emotion. Let us denote this proportion as n_i, $i = 1, 2, \ldots, 8$.

Two very important aspects for the calculation of the suicide risk index are both the number of words in each emotion and its proportion, since two people can have the same proportion in some emotion; however, the index will also be affected by the amount of words the person had in such emotion. Then, the final suicide risk index is calculated using the following formula:

$$SI = \sum_{i=1}^{8}(w_i N_i + n_i J_i) \qquad (1)$$

where, w_i, $n_i \in [0, 1]$, $N_i \in \mathbb{N}$ y $J_i \in \{1, 2, 3, 4, 5, 6, 7, 8\}$.

Finally, based on Bryan and Rudd (2006) and more particularly using the work of Gómez (2012), the classification of the suicide risk index will be: Slight, Moderate, Severe and Extreme. See Table 4 of Gómez (2012) for a detailed explanation of the suicide classification.

A general outline of the proposed methodology is presented below.

1: Hierarchy of emotions through AHP.

- Perform comparison of emotions with support from experts (psychologists). Generate matrix A of comparisons.
- Check consistency.
- Calculate weight of emotions.
- Obtain the hierarchy of emotions.

2: Obtention of tweets.

3: Opinion mining. Text analysis.

- Classification of the words obtained from tweets in the eight emotions (NRC).

4: Calculation of the Suicide Risk Index (IS).

- Classification of SI: Slight, Moderate, Severe and Extreme.

3. Results

In order to know the ideal weight for each of the eight emotions, the instrument shown in Annex 1 was applied to 20 psychologists from different parts of Mexico and these were randomly divided into three groups.

Matrix **A** of group 1 was given by:

	Joy	Trust	Fear	Surprise	Sadness	Disgust	Anger	Anticipation
Joy			1/9	1/5	1/9	1/9	1/9	1/9
Trust			1/7	1/7	1/9	1/9	1/9	1/9
Fear			1	5	1	7	7	7
Surprise			1/5	1	1/5	1/5	1/9	1/5
Sadness			1	5	1	1	1/5	1
Disgust			1/7	5	1	1	1	5
Anger			1/7	9	5	1	1	7
Anticipation			1/7	5	1	1/5	1/7	1

Matrix **A** of group 2 was given by:

	Joy	Trust	Fear	Surprise	Sadness	Disgust	Anger	Anticipation
Joy	1	1/3	1/5	1/3	1/7	1/7	1/7	1/3
Trust	3	1	1/5	1/5	1/7	1/5	1/7	1/3
Fear	5	5	1	5	1	1	1	3
Surprise	3	5	1/5	1	1/5	1/3	1/5	1/3
Sadness	7	7	1	5	1	5	1	3
Disgust	7	5	1	3	1/5	1	1/3	3
Anger	7	7	1	5	1	3	1	5
Anticipation	3	3	1/3	3	1/3	1/3	1/5	1

Matrix **A** of group 3 was given by:

	Jo	Tr	Fe	Su	Sa	Di	A	An n
Joy	1	1	1/5	1	1/7	1/7	1/5	1/3
Trust	1	1	1/3	1	1/7	1/3	1/5	1
Fear	5	3	1	5	1/5	5	5	9
Surprise	1	1	1/5	1	1/7	1/3	1/5	1
Sadness	7	7	5	7	1	7	3	7
Disgust	7	3	1/5	3	1/7	1	5	1
Anger	5	5	1/5	5	1/3	1/5	1	1/3
Anticipation	3	1	1/9	1	1/7	1	3	1

Using AHP, weight was calculated for each emotion and for each group of psychologists. The results are shown in Table 1.

Emotion	Group 1	2	3
Joy	0.01532	0.02475	0.03108
Trust	0.01532	0.03411	0.03900
Fear	0.32934	0.18618	0.22389
Surprise	0.04925	0.05861	0.03670
Sadness	0.14068	0.24604	0.36923
Disgust	0.13719	0.13641	0.12312
Anger	0.21840	0.23896	0.10806
Anticipation	0.09336	0.07494	0.06894

Table 1 Final weight using AHP
Source: Prepared by the authors

The next stage consists in calculating the consistency of the psychologists' decisions, that is, determining whether the decision makers have been consistent in their evaluations. Saaty, T. (2001) argues that when the consistency ratio (CR) is less than 0.1, it indicates that the judgments are within the recommended limits, are consistent and the process must be continued. The following is required to calculate the RC.

Geometric Consistency Index (CI):

$$CI = \frac{\lambda_{max} - n}{n-1},$$

where λ_{max} is the sum of all the maximum eigenvalues, calculated for each criterion, which were in turn obtained as the product of each of the eigenvalues by the total of the sum of the values of the column of each criterion (Saaty, 2001, 2009). And n is the number of criteria, that is, $n = 8$.

Random Consistency Index (RI):

$$RI = 1.98\frac{n-1}{n}.$$

Consistency Ratio (CR):

$$CR = \frac{CI}{RI}.$$

The results of the consistency ratio, for each group of psychologists, was: for group 1, the CR was 0.28786156, for group 2 the CR was 0.08820785 and for group 3 the CR was 0.22103277.

We can see that only for group 2 the consistency ratio is less than 0.1, which indicates that to continue with our process we must consider the weight granted by group 2. The final weight to consider in this work obtained with AHP and the ranking obtained are presented in Table 2.

Emotion	Weight w_i	Hierarchy J_i
Joy	0.02475	1
Trust	0.03411	2
Fear	0.18618	6
Surprise	0.05861	3
Sadness	0.24604	8
Disgust	0.13641	5
Anger	0.23896	7
Anticipation	0.07494	4

Table 2 Weight and Hierarchy
Source: Prepared by the authors

The final weight used to calculate the suicide risk index in addition to the accumulated weight are shown in Figure 1.

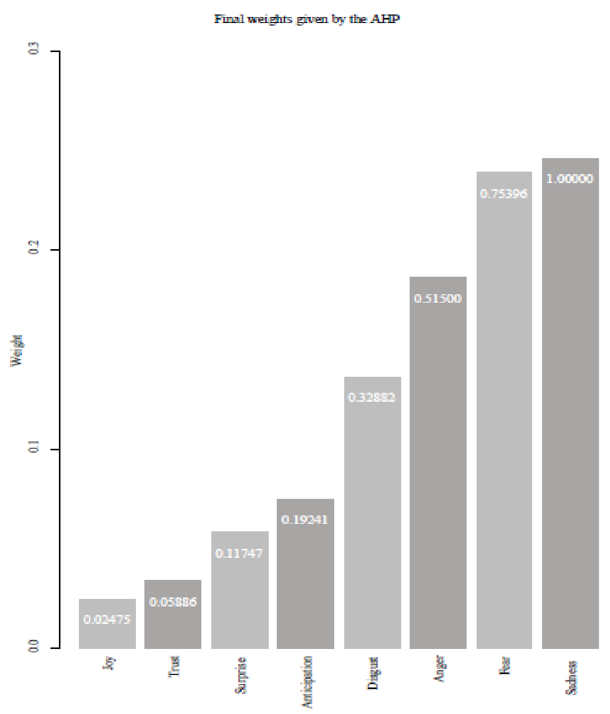

Figure 1 Final weights for each emotion found through AHP. In addition, weight accumulated by emotions are shown
Source: Prepared by the authors

As we can see, Sadness, Anger and Fear are the emotions that have the greatest effect on suicide risk, covering approximately 67% of total weight. Disgust and Anticipation contribute 21% and finally Surprise, Trust and Joy contribute 12%.

The classification of the Suicide Index (SI) proposed in this article is the following: Slight if SI <7, Moderate if 7 ≤ SI <11, Severe if 11 ≤ SI <15 and Extreme if SI ≥ 15.

Once having the weights and the hierarchy of the eight emotions given by the expert through AHP (Table 2), 177 people were considered for the study. Through the NRC analysis the tweets of these people were analyzed, and the words were counted in each of the main emotions.

This analysis was carried out using the R statistical package. To collect a sample of tweets, the library "twitteR" was used, which allows us to access the public API of twitter.com. A series of alpha-numeric codes is needed to access the twitter API and to obtain them, it is necessary to be registered on its website.

The first thing is to read the file and convert the tweets into a data.frame using the twListToDF() function. The analysis of emotions in this work only considers the original tweets of each person. The "syuzhet" library is also used, in which it is enough to pass a string to the get_nrc_sentiment function and it returns a data.frame with an estimate of the feeling shown in the text, which can be: anger, anticipation, disgust, fear, joy, sadness, surprise, trust, negative, positive. This library uses the NCR-Word-Emotion Association Lexicon, where words are associated with the eight basic emotions. Even in R, we can see how the words are classified in each emotion. Some important reference libraries are: "dplyr," "tidyr," "tidytext" and "tm."

Let us see an example.

On April 1, 2019, the news in Mexico began with the news of the suicide of musician Armando Vega-Gil, who left a note on his Twitter account. This note contains, among others, the phrase "His orphanhood is a terrible way to violate it, but a terrible ending is better than a terror without an end" (Su orfandad es una manera terrible de violentarlo, pero más vale un final terrible que un terror sin final) (Vega-Gil, A. 2019). This section presents the identification of emotions expressed in the note through the following R code to classify the tweet:

get_nrc_sentiment("Su orfandad es una manera terrible de violentarlo, pero más vale un final terrible que un terror sin final",language = "spanish")

The identified emotions, with quantity of words per emotion, and their proportion, as well as contribution to the SI are:

Emotion	N_i	n_i	w_i	J_i	Contribution to SI
Anger	2	0.1818	0.23896	7	1.7506
Anticipation	1	0.0909	0.07494	4	0.4386
Disgust	2	0.1818	0.13641	5	1.1819
Fear	3	0.2727	0.18618	6	2.1949
Joy	0	0.0000	0.02475	1	0.0000
Sadness	2	0.1818	0.24604	8	1.9466
Surprise	0	0.0000	0.05861	3	0.0000
Trust	1	0.0909	0.03411	2	0.2159
Total words considered	**1**			**SI:**	**7.7286**

ISSN 2414-4835

Note that both w_i and J_i have already been defined in Table 2 and how to calculate the contribution of each emotion to the SI is given in (1). According to these calculations, the phrase presented expresses a level of risk of moderate suicide.

Thus, for each person and the tweets that they have published, the total number of words in each emotion (N_i) was counted and their proportion (n_i) was calculated. In addition, we established the restriction that there should be at least 15 words in total to be able to quantify its suicide risk index. Note that the number of tweets for each person was not quantified in this work. Finally, this person was classified according to the index obtained in Slight, Moderate, Severe and Extreme.

Example *Table 3 shows the results of the proposed methodology considering four arbitrary persons. According to their tweets, the number of words for each emotion was counted using the NCR-Word-Emotion Association Lexicon and their respective ´SI was calculated using equation (1) and the data in Table 2.*

Person	P1		P2		P3		P4	
	N_i	n_i	N_i	n_i	N_i	n_i	N_i	n_i
Joy	0	0	3	0.0566	1	0.0455	9	0.2571
Ttust	0	0	10	0.1887	2	0.0909	11	0.3143
Fear	17	0.3269	15	0.283	4	0.1818	1	0.0286
Surprise	0	0	1	0.0189	1	0.0455	2	0.0571
Sadness	9	0.1731	9	0.1698	7	0.3182	1	0.0286
Disgust	14	0.2692	2	0.0377	1	0.0455	1	0.0286
Anger	12	0.2308	9	0.1698	5	0.2273	1	0.0286
Anticipation	0	0	4	0.0755	1	0.0455	9	0.2571
Total	52	1	53	1	22	1	35	1
Index		6.4644		13.4301		10.0247		5.0258
Classification		Extreme		Severe		Moderate		Slight

Table 3 Example of calculation of suicide index and its classification
Source: Prepared by the authors

As we can see in Table 3, both the number of words in each emotion and its proportion are important for obtaining the index. The full results for the 177 people are shown in Annex 2. The names are omitted for privacy reasons.

Thus, using sentiment analysis and the AHP, a suicide risk index has been constructed, allowing to rank the emotions expressed by Twitter users. This will help experts to put red flags or alarms on those whose index is very high.

It is important to clarify that the classification given for the index is arbitrary and was constructed considering the hierarchy of emotions obtained from psychologists. However, to analyze the sensitivity of the result of the proposed classification, a cluster analysis was carried out, seeking to find four homogeneous subgroups among the data considering a hierarchical grouping, using the centroid as a link function and as a measure of dissimilarity to the Euclidean distance. See James G., Witten D., Hastie T. & Tibshirani R., (2017) for more details. The percentage of equal classification between the one provided by the cluster analysis and that obtained in this work is 97.17514%. See Figure 2.

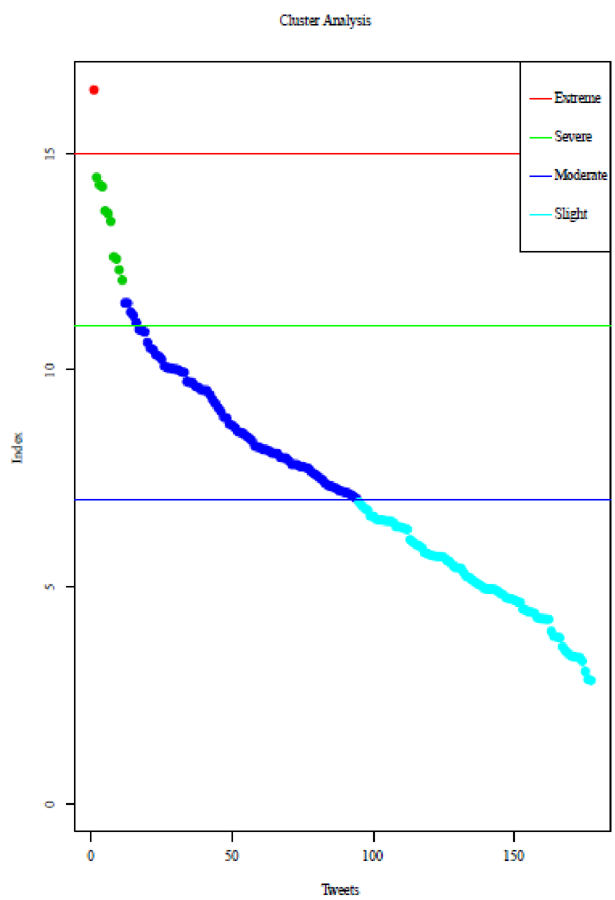

Figure 2 Classification of suicide risk index for 177 people
Source: Prepared by the authors

As we can see, a person with extreme suicide risk was detected, representing 0.56% of the total number of people. 8.47% were classified with severe suicide risk, while 44.08% and 46.89% were detected with moderate and slight risk, respectively.

June 2019 Vol.5 No.15 1-13

4. Annexes

INSTRUCCIONES: Al analizar las pláticas de un paciente de salud mental, se pueden identificar algunas emociones que permitirían cuantificar el riesgo percibido que tiene ésta o éste de atentar contra su vida.

A continuación se presentan parejas de emociones que han sido detectados en una sola plática (considere cada par como una plática separada). Se le pide que usted establezca cuál de ellas considera daría dar más indicación de riesgo de suicido de su paciente, para ello deberá seleccionar el número más cercano a la emoción que mejor describa esta cualidad, usando la siguiente escala:

1 **igualmente** importante
3 **ligeramente** más importante
5 **notablemente** más importante
7 **demostrablemente** más importante
9 **absolutamente** más importante

Por ejemplo, si usted identifica en su paciente emociones de enojo y tristeza, y considera que la tristeza expresada es **ligeramente** más importante que los niveles de enojo, para definir el riesgo que tiene el paciente de cometer suicidio, entonces seleccione el número 3 que está más cercano a esta emoción:

Emoción				Nivel de Importancia					Emoción
Tristeza	9	7	5	~~3~~	1	3	5	7	9	Enojo

Por favor, realice este ejercicio con las siguientes parejas de emociones.

Emoción					Nivel de Importancia					Emoción
Alegría	9	7	5	3	1	3	5	7	9	Confianza
Alegría	9	7	5	3	1	3	5	7	9	Miedo
Alegría	9	7	5	3	1	3	5	7	9	Sorpresa
Alegría	9	7	5	3	1	3	5	7	9	Tristeza
Alegría	9	7	5	3	1	3	5	7	9	Aversión
Alegría	9	7	5	3	1	3	5	7	9	Enojo
Alegría	9	7	5	3	1	3	5	7	9	Anticipación
Confianza	9	7	5	3	1	3	5	7	9	Miedo
Confianza	9	7	5	3	1	3	5	7	9	Sorpresa
Confianza	9	7	5	3	1	3	5	7	9	Tristeza
Confianza	9	7	5	3	1	3	5	7	9	Aversión
Confianza	9	7	5	3	1	3	5	7	9	Enojo
Confianza	9	7	5	3	1	3	5	7	9	Anticipación
Miedo	9	7	5	3	1	3	5	7	9	Sorpresa
Miedo	9	7	5	3	1	3	5	7	9	Tristeza
Miedo	9	7	5	3	1	3	5	7	9	Aversión
Miedo	9	7	5	3	1	3	5	7	9	Enojo
Miedo	9	7	5	3	1	3	5	7	9	Anticipación
Sorpresa	9	7	5	3	1	3	5	7	9	Tristeza
Sorpresa	9	7	5	3	1	3	5	7	9	Aversión
Sorpresa	9	7	5	3	1	3	5	7	9	Enojo
Sorpresa	9	7	5	3	1	3	5	7	9	Anticipación
Tristeza	9	7	5	3	1	3	5	7	9	Aversión
Tristeza	9	7	5	3	1	3	5	7	9	Enojo
Tristeza	9	7	5	3	1	3	5	7	9	Anticipación
Aversión	9	7	5	3	1	3	5	7	9	Enojo
Aversión	9	7	5	3	1	3	5	7	9	Anticipación
Enojo	9	7	5	3	1	3	5	7	9	Anticipación

Annex 1 Instrument applied to psychologists (AHP)

Person	Index	Criterion	no.of words	Cluster	Classification
1	16.46437231	Extreme	52	1	1
2	14.44026556	Severe	72	2	2
3	14.27139233	Severe	43	2	2
4	14.22809603	Severe	63	2	2
5	13.66806642	Severe	53	2	2
6	13.60952041	Severe	49	2	2
7	13.43065509	Severe	53	2	2
8	12.60642571	Severe	70	2	2
9	12.56363553	Severe	47	2	2
10	12.30704281	Severe	57	2	2
11	12.07050333	Severe	60	2	2
12	11.54512905	Severe	42	3	2
13	11.54131388	Severe	49	3	2
14	11.33339163	Severe	43	3	2
15	11.25557448	Severe	29	3	2
16	11.09227	Severe	19	3	2
17	10.93261636	Moderate	44	3	3
18	10.90664769	Moderate	52	3	3
19	10.87794	Moderate	50	3	3
20	10.63340474	Moderate	38	3	3
21	10.50041143	Moderate	56	3	3
22	10.46378	Moderate	16	3	3
23	10.34987238	Moderate	21	3	3
24	10.31776778	Moderate	36	3	3
25	10.24270286	Moderate	35	3	3
26	10.08530105	Moderate	19	3	3
27	10.05030667	Moderate	30	3	3
28	10.03987	Moderate	40	3	3
29	10.02473	Moderate	22	3	3
30	10.01814077	Moderate	39	3	3
31	9.99973	Moderate	30	3	3
32	9.954913333	Moderate	24	3	3
33	9.940979048	Moderate	21	3	3
34	9.730943158	Moderate	19	3	3
35	9.71309	Moderate	26	3	3
36	9.704547037	Moderate	54	3	3
37	9.61961	Moderate	33	3	3
38	9.596262703	Moderate	37	3	3
39	9.539871395	Moderate	43	3	3
40	9.529354706	Moderate	34	3	3
41	9.528781818	Moderate	44	3	3
42	9.432493913	Moderate	23	3	3
43	9.320565714	Moderate	35	3	3
44	9.224845	Moderate	64	3	3
45	9.124087619	Moderate	21	3	3
46	9.03949	Moderate	36	3	3
47	8.904870968	Moderate	62	3	3
48	8.888157419	Moderate	31	3	3
49	8.746415882	Moderate	17	3	3
50	8.715425882	Moderate	17	3	3
51	8.667878592	Moderate	71	3	3
52	8.573004783	Moderate	23	3	3
53	8.554465172	Moderate	29	3	3
54	8.53069	Moderate	41	3	3
55	8.47313	Moderate	50	3	3
56	8.42414	Moderate	20	3	3
57	8.365777143	Moderate	28	3	3
58	8.237961613	Moderate	62	3	3
59	8.223028421	Moderate	38	3	3
60	8.199147778	Moderate	27	3	3
61	8.16393	Moderate	22	3	3
62	8.15973	Moderate	32	3	3
63	8.13332	Moderate	20	3	3
64	8.080376957	Moderate	23	3	3
65	8.075191081	Moderate	37	3	3
66	8.067707273	Moderate	33	3	3
67	7.988098889	Moderate	45	3	3
68	7.96896	Moderate	21	3	3
69	7.968677647	Moderate	17	3	3
70	7.903912593	Moderate	27	3	3
71	7.82403	Moderate	20	3	3
72	7.820003077	Moderate	26	3	3
73	7.817166667	Moderate	18	3	3
74	7.771593077	Moderate	26	3	3
75	7.768275263	Moderate	38	3	3
76	7.744782121	Moderate	33	3	3
77	7.723231905	Moderate	21	3	3
78	7.651872174	Moderate	23	3	3
79	7.601238421	Moderate	19	3	3
80	7.562283529	Moderate	17	3	3
81	7.505373333	Moderate	27	3	3
82	7.461027143	Moderate	42	3	3
83	7.376900909	Moderate	33	3	3
84	7.33316	Moderate	25	3	3
85	7.317443333	Moderate	36	3	3
86	7.28942	Moderate	40	3	3
87	7.259757619	Moderate	21	3	3
88	7.207105854	Moderate	41	3	3
89	7.194968936	Moderate	47	3	3
90	7.173777692	Moderate	26	3	3
91	7.16004973	Moderate	37	3	3
92	7.124982759	Moderate	29	3	3
93	7.078643871	Moderate	31	3	3
94	7.029951429	Moderate	21	3	3
95	6.94425	Slight	30	4	4
96	6.864024211	Slight	38	4	4
97	6.801047273	Slight	22	4	4
98	6.76343	Slight	25	4	4
99	6.627654444	Slight	18	4	4
100	6.625444286	Slight	28	4	4
101	6.551581765	Slight	34	4	4
102	6.538346923	Slight	26	4	4
103	6.536273913	Slight	46	4	4
104	6.522699474	Slight	19	4	4
105	6.513644706	Slight	17	4	4
106	6.511258889	Slight	18	4	4
107	6.48612	Slight	20	4	4
108	6.38015	Slight	16	4	4
109	6.379241176	Slight	17	4	4
110	6.364651429	Slight	28	4	4
111	6.337802308	Slight	26	4	4
112	6.320157097	Slight	31	4	4

Person	Index	Criterion	no.of words	Cluster	Classification
113	6.082824615	Slight	26	4	4
114	6.02797	Slight	32	4	4
115	5.97112	Slight	25	4	4
116	5.950363529	Slight	17	4	4
117	5.90634	Slight	19	4	4
118	5.79138	Slight	16	4	4
119	5.7658	Slight	50	4	4
120	5.732076667	Slight	24	4	4
121	5.712487949	Slight	39	4	4
122	5.697153529	Slight	34	4	4
123	5.69508	Slight	20	4	4
124	5.68941	Slight	16	4	4
125	5.672806923	Slight	26	4	4
126	5.60813	Slight	16	4	4
127	5.577472105	Slight	19	4	4
128	5.4957	Slight	20	4	4
129	5.444047778	Slight	18	4	4
130	5.436903846	Slight	26	4	4
131	5.421333333	Slight	30	4	4
132	5.318872222	Slight	27	4	4
133	5.229688148	Slight	27	4	4
134	5.20867	Slight	24	4	4
135	5.14979	Slight	20	4	4
136	5.107161538	Slight	26	4	4
137	5.059582381	Slight	21	4	4
138	5.025801429	Slight	35	4	4
139	4.966341053	Slight	19	4	4
140	4.948511053	Slight	19	4	4
141	4.943781053	Slight	19	4	4
142	4.940972632	Slight	19	4	4
143	4.93355	Slight	25	4	4
144	4.89686	Slight	32	4	4
145	4.838891613	Slight	31	4	4
146	4.80805	Slight	26	4	4
147	4.747371176	Slight	17	4	4
148	4.727512222	Slight	18	4	4
149	4.71598	Slight	16	4	4
150	4.68481	Slight	20	4	4
151	4.647951176	Slight	17	4	4
152	4.6317	Slight	20	4	4
153	4.478691111	Slight	18	4	4
154	4.455943158	Slight	19	4	4
155	4.42102	Slight	16	4	4
156	4.413330588	Slight	17	4	4
157	4.386117059	Slight	17	4	4
158	4.287521905	Slight	21	4	4
159	4.266465217	Slight	23	4	4
160	4.258736667	Slight	24	4	4
161	4.253971818	Slight	22	4	4
162	4.248257273	Slight	22	4	4
163	3.96848	Slight	16	4	4
164	3.850892222	Slight	18	4	4
165	3.840469091	Slight	22	4	4
166	3.818285714	Slight	21	4	4
167	3.610366667	Slight	24	4	4
168	3.515431765	Slight	17	4	4
169	3.454504211	Slight	19	4	4
170	3.402535294	Slight	17	4	4
171	3.386461765	Slight	17	4	4
172	3.370748235	Slight	17	4	4
173	3.364708889	Slight	18	4	4
174	3.278131053	Slight	19	4	4
175	3.046477647	Slight	17	4	4
176	2.86458	Slight	25	4	4
177	2.83408	Slight	20	4	4

Annex 2 Classification of suicide index

5. Acknowledgments

The authors acknowledge and thank the support of psychologist Martha Mirana González Gómez and the psychologists who participated in the First National Meeting of Intedisciplinary Research Code 27, where they kindly collaborated in obtaining the final weights of the AHP.

6. Conclusions

This paper proposed an alternative to detect suicide attempts of people through their publications on the social network Twitter.

The proposed methodology is based on the analysis of emotions and the Analytical Hierarchical Process, quantifying the importance of basic emotions. The decisions made by psychologists are perfectly acceptable, since the consistency ratio was 0.0882 for the process, as recommended by Saaty (2009). Thus, the final weights obtained by the AHP for each emotion can be replicated for future research.

In this investigation the number of words in each emotion was collected through the NCR-Word-Emotion Association Lexicon using the statistical language R, which resulted to be a friendly and easy-to-use tool.

The results obtained with respect to the 177 people considered in the study indicate that more than 90% were classified with slight and moderate risk and there was no suicidal intention in them. However, and for health purposes, attention should be given to those classified as severe and much more to those with extreme risk. The measures must be precise and on time.

Given the high rates of suicide presented in recent years, it has become a prevailing necessity to develop a tool that allows to detect in time suicidal intentions. Granted the frequent use of social media, they can become an ally for suicide prevention by incorporating them into methodologies such as the one proposed in this research. The present work proves to be an easily accessible tool in which different public organizations can replicate the methods to prevent suicide in Mexico.

References

Asdalifah Talibe, Aaturrawiah Ali Omar & Tong Sin Bei. (2014). *Evaluation of depression criteria using Analytic Hierarchy Process: a case study* on University Malaysia Sabah sciences' Schools. Borneo Science; 35:1-9.

Bing Liu. (2012). *Sentiment analysis and opinion mining.* Morgan & Claypool Publishers.

Brujita. (2016). *Teoría de las emociones: Robert Plutchik.* Accessed in June 19, 2019: https://www.lawebdelasbrujas.com/teoria-de-las-emociones-robert-plutchik/

Bryan C.J. & Rudd M. D. (2006). *Advances in the assessment of suicide risk.* J Clin Psychol; 62:85-200.

Cano-Vindel A. & Miguel-Tobal J. J. (2001). *Emociones y Salud. Ansiedad y Estr´es*;7(2-3):111-121.

Gómez, A. C. (2012). *Evaluación del riesgo de suicidio: enfoque actualizado.* Rev. Med. Clin. Condes;23(5):607-615.

González-Ganzábal, F. (2016). *Aspectos fundamentales del comportamiento suicida y su prevención.* Accessed in June 19, 2019:https://repositorio.unican.es/xmlui/bitstream/handle/10902/8921/Gonzalez 20Ganzabal 20F..pdf?sequence=4&isAllowed=y

Guntuku, S. C., Yaden, D. B., Kern, M. L., Ungar, L. H.,& Eichstaedt, J. C. (2017). *Detecting depression and mental illness on social media: an integrative review*. Current Opinion in Behavioral Sciences;18:43–49.

Hernández-Urbay, D. Sin Fecha. *Suicidio y estados emocionales en diferentes etapas de la vida.* Accessed in June 19, 2019: https://www.monografias.com/docs110/suicidio-y-estados-emocionales-diferentes-etapas-vida/suicidio-y-estados-emocionales-diferentes-etapas-vida.shtml

INEGI. (2018). Comunicado de prensa núm. 410/18 7 de septiembre de 2018, página 1/8. *Estadísticas a propósito del día mundial para la prevención del suicidio*. (datos nacionales). Accessed in June 19, 2019: http://www.beta.inegi.org.mx/contenidos/saladeprensa/aproposito/2018/suicidios2018_Nal.pdf

James G., Witten D., Hastie T. & Tibshirani R. (2017). *An Introduction to Statistical Learning with Applications in R.* Springer New York Heidelberg Dordrecht London.

Jamil, Z., Inkpen, D., Buddhitha, P., & White, K. (2017). *Monitoring Tweets for Depression to Detect At-risk Users.* Universit´e d'Ottawa/University of Ottawa.

Jiménez-Ornelas, R. A., & Cardiel-Téllez, L. (2013). *El suicidio y su tendencia social en México: 1990-2011*. Papeles de poblaci´on;19(77): 205-229. Accessed in April 09, 2019: http://www.scielo.org.mx/scielo.php?script=sci_arttext&pid=S1405-74252013000300012&lng=es&tlng=es.

https://www.redalyc.org/pdf/112/11228794009.pdf

Nadeem, M. *Identifying depression on Twitter.* (2016). ArXiv Preprint ArXiv:1607.07384.

OMS. (2018). *Suicidio.* Accessed in April 09, 2019: https://www.who.int/es/news-room/fact-sheets/detail/suicide

Orabi, A. H., Buddhitha, P., Orabi, M. H., & Inkpen, D. (2018). *Deep Learning for Depression Detection of Twitter Users.* In Proceedings of the Fifth Workshop on Computational Linguistics and Clinical Psychology: From Keyboard to Clinic: 88–97.

Piqueras Rodríguez, José Antonio, Ramos Linares, Victoriano, Martínez González, Agustín Ernesto, Oblitas Guadalupe, Luis Armando. (2009). *Emociones negativas y su impacto en la salud mental y f´isica.* Suma Psicológica [en linea] 2009, 16 (Diciembre-Sin mes): Accessed in June 19, 2019: http://www.redalyc.org/articulo.oa?id=134213131007.ISSN 0121-4381

Plutchik, R. (2001). *The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice*. American scientist; 89(4):344-350.

Reece, A. G., & Danforth, C. M. (2017). *Instagram photos reveal predictive markers of depression.* EPJ Data Science; 6(1):15.

Saaty, T. (2009). *Extending the Measurement of Tangibles to Intangibles*. In: International Journal of Infor- mation Technology & Decision Making; 8(1):7-27.

Saaty, T. (2008). *Decision making with the analytic hierarchy process*. Int. J. Services Sciences, 1(1), Inders- cience Enterprises Ltd, Ginebra, Suiza; 83-98.

Saaty, T. (2003). *Decision-Making with the AHP: Why is the principal eigenvector necessary*. European Journal of Operational Research;145(1):85-91.

Saaty, T. (2001). *The Analytic Network Process. In: Decision Making with the Analytic* Network Process. Pittsburg University Press;1-26.

Saaty, T. (1980). *The Analytic Hierarchy Process.* McGraw Hill. International, Pittsburgh, United States of America.

Saif M. & Turney, P. (2013). *Crowdsourcing a Word-Emotion Association Lexicon*, Computational Intelligence;29(3):436-465.

Simone Belli & Lupicinio ´Íñiguez-Rueda. (2008). *El estudio psicosocial de las emociones: una revisi´on y discusi´on de la investigaci´on actual*;Psico;39(2):139-151.

Stanford Children's Health. Sin fecha. *Suicidio en adolescentes.* Accessed in June 19, 2019: https://www.stanfordchildrens.org/es/topic/default?id=suicidio-de-adolescentes-90-P05694

Vega-Gil, Armando. (2019). *Nota Suicida.* Twitter. Accessed in April 04, 2019: https://twitter.com/ArmandoVegaGil/status/1112666222951391233