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#europehappinessmap: A Framework for Multi-Lingual Sentiment Analysis via Social Media Big Data (A Twitter Case Study)

Mustafa Coşkun * and Meltem Ozturan

Department of Management Information Systems, Bogazici University, 34470 Istanbul, Turkey; ozturanm@boun.edu.tr

* Correspondence: mustafa.coskun@boun.edu.tr; Tel.: +90-505-741-7058

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Abstract: The growth and popularity of social media platforms have generated a new social interaction environment thus a new collaboration and communication network among individuals. These platforms own tremendous amount of data about users' behaviors and sentiments since people create, share or exchange their information, ideas, pictures or video using them. One of these popular platforms is Twitter, which via its voluntary information sharing structure, provides researchers data potential of benefit for their studies. Based on Twitter data, in this study a multilingual sentiment detection framework is proposed to compute European Gross National Happiness (GNH). This framework consists of a novel data collection, filtering and sampling method, and a newly constructed multilingual sentiment detection algorithm for social media big data, and tested with nine European countries (United Kingdom, Germany, Sweden, Turkey, Portugal, The Netherlands, Italy, France and Spain) and their national languages over a six year period. The reliability of the data is checked with peak/troughs comparison for special days from Wikipedia news lists. The validity is checked with a group of correlation analyses with OECD Life Satisfaction survey reports', Euro-Dollar and other currency exchanges, and national stock market time series data. After validity and reliability confirmations, the European GNH map is drawn for six years. The main problem addressed is to propose a novel multilingual social media sentiment analysis framework for calculating GNH for countries and change the way of OECD type organizations' survey and interview methodology. Also, it is believed that this framework can serve more detailed results (e.g., daily or hourly sentiments of society in different languages).

Keywords: sentiment detection; Europe happiness; opinion mining; Twitter; big data; social media

1. Introduction & Literature Review

The rise of social broadcasting technologies has led to open data access for researchers. Most of the popular social media platforms allow researchers to collect valuable public data for free and to conduct studies based on those data [1,2]. Also, the use of social media has diffused widely in society with recent statistical data showing high penetration rates [3–6]. As it is mentioned by Quan-Haase and Young [7] users tend to embrace new media and adopt them as part of their communication repertoire. To some degree this is an advantage at the current stage of studying social media, as it leaves much room for exploring approaches to address research questions [8,9]. These studies are inspiring about the social media and big data analysis concepts, then, to this respect, a deep literature review was done on social media and big data analysis concepts at the beginning of this study. First of all, common and popular social media platforms and the studies about them were investigated. Then, chronological trending topics analysis was done. The results showed that although 50% of the users of Twitter are from the Asia Pacific region, when the ratios of users to country populations are examined, Twitter is in fact mostly used in European and North American countries (https://www.statista.com/statistics/303684/regional-twitter-user-distribution/). Also, it has been the most available data source for the social media researchers due to its related Application Programming Interfaces (APIs) that make it easy to collect data. After discussing social media studies, a common trend on user generated content analysis was detected and also was seen that sentiment analysis on these platforms is an emerging topic. Thus, Twitter sentiment analysis studies in the literature were deeply analyzed. Specifically, the following ideas for this study can be summarized from the literature review as follows:

- Dictionary-based text analysis is the most common and approved method [10–17].
- Embedding emoticons to the analysis helps to improve results' quality [13,18,19].
- Geo-location usage is a conflict for this kind of analysis [17,19].
- Standardization and filtering are the main problem for generalizability issues of the results. This problem should be focused most [15,20].
- Data collection methods have not been mentioned in the studies. Generally, researchers mention the collected data but not how to collect.
- Generally English language used in the studies. Also, if English is not used, then researchers use only one dictionary and analyze only one language and one country.

1.1. Cultural Well-Being and Life Satisfaction Studies

Since the sentiment analysis on social media has been found a trending topic among information systems and cyber-psychology researchers [21–23], this study aims to focus on this topic. However, analyzing public sentiments is not a new methodology for scientist. Thus, a deep literature review was done on cultural well-being and life satisfaction studies to find out general tendency and possible contribution areas. As a result of the analysis of cultural well-being, cultural differences and life satisfaction studies, it can be concluded that this kind of studies are generally made with survey [24–27], interviews and other types of qualitative methods [27–29]. On the other hand, social media sentiment analysis studies have a tendency to be popular in the literature. Combining these two type of studies, it is believed that, a multicultural and multidimensional study, which compares and contrasts the cultural and lingual differences, would contribute to information systems and social sciences literature. Moreover, if a novel methodology for data collection and analysis can be conducted, this framework can be useful for not only social media analysis but also for researchers working on social media.

1.2. Ethics on Social Media Studies

The last part of the literature review is about ethical issues. Actually, the ethical aspects of using social media data for researches are still not clearly defined even though the structure of the data is publicly available. Related to ethical issues, it is seen that six studies [30–35] were approved by their authors' corresponding Institutional Review Boards (IRB) and five [34,36–39] received consent from participants prior to data analysis. However, Youyou, et al. [40] stated that IRB approval is not essential for using the data. Similarly, in their study, Chancellor, et al. [41] did not collect IRB approval, because their study used Instagram data without personally identifiable information. In addition, several studies [32,42–45] showed that, anonymizing user profile data is another method for this kind of social media studies. For instance, changing the names and usernames in tweets with other texts is a method of anonymization [42,44,46]. Based on these studies, it can be stated that, there is still not a common approach for handling ethical issues among researchers.

It is obvious that this issue is still unstable and fuzzy [47], but in order to contribute social media studies and science itself, public data should be used for scientific manner. Thus, the best approach to reducing the ethical issues of accessing to and using personal information is to anonymize the collected data sets and filtering the result to state a common (public) result (e.g., Gross National Happiness—GNH).

1.3. Results of Literature Review

To conclude, a deep literature review was conducted in this study to discover trending topics, possible contributions of the related studies and their future recommendations to form a basis for the research of this study. Therefore, to the best of authors' knowledge, it can be concluded that;

- There is not a multi-lingual framework for Twitter sentiment analysis.
- Lexicon-based (dictionary-based) sentiment analysis is still most popular instead of machine learning, classification and clustering.
- Multicultural comparison of social media data on sentiment analysis has not been done yet.
- Data collection is the least mentioned part in articles, while proposing a novel method for this issue can be very supportive for the academics.
- The user Twitter features such as follower count, friends count, Twitter age, number of Tweets have not been taken into account yet in terms of possible relations of them.
- Whereas business effect and value are mentioned in several studies, the result of a multicultural sentiment analysis and GNH map of a continent have not considered by the researchers yet.
- Some of the dictionaries aimed to be used in this study are mentioned in some studies but have not been used all together yet (possibly because of huge work requirement).
- Big data studies are becoming very popular on sentiment analysis but have not been defined well yet.
- English is very popular and people usually use the LICW dictionary, but except for a few local small scale studies, other languages have not been examined with big data analysis to detect sentiments.
- Validation and accuracy of findings is not a concept for sentiment analysis studies while it should be.
- Anonymizing users' information, converting the info with other texts and filtering out results to conclude a general result are the frequent methods for ethical consideration on social media studies.

2. Research Questions and Scientific Value

The main research question stated for this study is:

> *"Is the social media big data appropriate for the sentiment analysis (instead of surveys or interviews) to draw a happiness map of Europe?"*

Moreover, combining with "designing a social media big data sentiment analysis algorithm" for the aim of the study the following objective is stated:

> *"To design, develop, implement and evaluate a framework for multi-lingual sentiment analysis* via *social media big data for calculating Gross National Happiness (GNH) levels of European Countries"*

In the way of main purpose, sentiment analysis framework is implemented for determining the happiness polarities of European citizens through answering the following four research questions:

- Is there face validity when the polarities determined by sentiment analysis framework are compared with Stock Market Index and Exchange Rates?
- Is there convergent validity when the GNH results of the sentiment analysis framework and GNH survey results of Organization for Economic Cooperation and Development (OECD) report are compared?

- Is there data reliability when the peaks/troughs of the graphs of sentiment analysis framework are compared with specific dates obtained from news archives?
- What are the GNH polarities of European countries in accordance with the proposed Twitter sentiment analysis framework?

The first two questions are about the validation and third question is about the reliability of sentiment detection algorithm and social media data collection and filtering methodology (social media data analysis framework at all). The last is for exploring the GNH polarities of related countries.

3. Materials and Methodology

Ferraro [48] defines the term "framework" as; "in general, a framework is a real or conceptual structure intended to serve as a support or guide for the building of something that expands the structure into something useful". In addition, according to Duncan [49] a framework may be for a set of functions within a system and how they interrelate. Combining these, a framework is generally more comprehensive than a protocol and more prescriptive than a structure. Thus, the original scientific contribution of this study is intended to "propose an integrated framework (not only an opinion mining algorithm but also data collection and sampling techniques) via social media big data analysis for sentiment calculation". In addition to all the sequences of this proposed integrated framework (design, development, implementation and evaluation), a unique data collection methodology and a purposive sampling technique for the sentiment analysis social media big data are proposed as demonstrated in the following subsections.

3.1. Design of Sentiment Analysis Algorithm

As an emerging and promising research area, text mining for sentiment analysis has been extensively studied [50–53], where sentiment analysis is used for text classification tasks [54,55]. Li and Wu [56] summarize that existing sentiment calculation approaches fall into two types: machine learning-based approaches [51,52] and semantic orientation based approaches [52,53,57]. While text sentiment analysis is very popular, the literature has a big gap on multicultural and multilingual studies.

Moreover, in the literature, sentiment analysis studies can be grouped into two main categories: "supervised" and "unsupervised". The pre-defined words and their polarities are used in one, on the other hand, the other classifies the most frequent words and drives a dictionary with them. However, Thelwall, et al. [58] state that similar results and accuracy rates are achieved from those two methods, since big data eliminates the noise of data and extreme cases which cause the differences between those two methods. Due to these facts, predefined dictionaries are used in this study instead of creating new dictionaries from the data set, which would possibly take the progress, workload and timeline of the project to unmanageable levels.

Also, it is stated by Thelwall, Buckley and Paltoglou [58] that dual output for the sentiment analysis of blogging short texts concludes more accurate results. Therefore, the polarity of the tweets in the algorithm is better to be calculated not in one (binary classification) dimension but in two dimensions (positive, negative).

The language dictionaries for the algorithm is taken from a short text sentiment analysis tool (SentiStrength) created by Thelwall, et al. [59]. This tool was developed for short text analysis and is still on testing phase due to accuracy concerns. The sentiment dictionaries of this study are found to be appropriate for our study since some of the dictionaries were previously tested with different platforms for single language studies [60–67].

Additionally, Pfitzner, et al. [68] conclude that the sentences ending with a "question mark (?)" should not be included in sentiment analysis. Because those texts do not represent the feelings of the people who write them. To this end, in this study the tweets ending with or including "question mark" are removed in the algorithm.

In addition to these common text sentiment analysis concepts, which are used by different social median platforms than Twitter (blogs, Facebook etc.) in different languages, it is a well-known fact that limiting the polarity scale for analyzed texts in a range (e.g., −5 to +5) is appropriate for balancing the standard deviation of total (or filtered) score.

Moreover, Rudra, et al. [69] state that idioms usage in Twitter is 9% and this percentage would increase from 21.88% (in mentioned network user groups) to 49.57% (in subscription network user groups). Thus, since the dictionaries of the algorithm include idioms, idiom looking up operations are embedded in the proposed algorithm to increase the validity and accuracy.

Lastly, the booster and negating words have an effect on the polarities of the neighbor words. Therefore, this calculation is included in the algorithm, too.

As a conclusion of these sentiment analysis literature survey and using the text mining dictionaries a new sentiment analysis algorithm was developed as shown with pseudocodes in Figure 1.

1) For each tweet
   i. If the tweet is a question
      - ending with a question mark
      - using question words from dictionary

      check the "question" flag of it in database
   ii. If the tweet has any irony term (from dictionary) check the "irony" flag of it in database
   iii. Explode sentences to words, punctuations and emoticons
   iv. Find the idioms in the tweets, calculate their sentiments
   v. For each words and emoticons
      - Find the sentiment polarity (in a range of −5 to +5) from dictionary
      - If whole word could not be found in dictionary, check root from rooting words (dictionary contains words with roots, for instance, instead of "ağlamak", dictionary contains "ağla*")
      - If the word is "booster word" (from dictionary) increase (or decrease) the following word's sentiment polarity
      - If the word is "negating word" (from dictionary) flip the following word's sentiment
   vi. For each emoticons find the sentiment polarity from emoticon dictionary
   vii. Store negative and positive sum of polarities

2) Check all database and crop all polarities more than 5 to 5 for positive sentiment score and less than −5 to −5 for negative sentiment score

3) Check all database and change 0 to −1 for negative sentiment score and change 0 to +1 for positive sentiment score

Figure 1. Proposed Sentiment Analysis (Polarity Calculation) Algorithm.

3.2. GNH Calculation for Countries

In the second half of the 20th century, Bhutan, as a South Asian country stated that "Gross National Happiness is more important than Gross National Product (GDP)" and started a visionary study at the governmental (kingdom) level for calculating GNH [70]. This country level work can be accepted as the first GNH dominated study under United Nations, because the previous studies were mainly based on GDP. Therefore, since social media can be defined as a screaming platform for society to define public feeling, the idea of "a country level happiness measurement methodology can be defined and tested via social media big data" inspired this study. For the calculation of GNH for European calculation, a unique (but combined by a deep literature survey) algorithm was created.

3.3. Gross National Happiness Calculation Algorithm

Big data of this proposed social media analysis framework constitutes of daily tweets of the users coming from chosen countries (filtering options is explained in related section). GNH of each country is calculated by considering the daily tweets' happiness polarities of the users of the related country; therefore, for GNH Calculation in Tweets Domain (GNH-TD) operation, tweets of users are analyzed in terms of their polarities. For GNH Calculation in Tweets Domain (GNH-TD) operation, tweets of users are analyzed in terms of their polarities. In his novel GNH study, Kramer [71] used a Linguistic Inquiry and Word Count (LIWC) dictionary, and stated that this dictionary has different number of positive and negative words (and also their polarities are different at total). Thus, it is claimed that the potential for positive and negative word use is not equivalent. To cope with this problem and to generate a metric that is interpretable independent of language and dictionary, adapting from Kramer [71], the idea of "how much standard deviation away from mean?" is used in the GNH-TD algorithm. The proposed GNH-TD calculation algorithm is shown in Figure 2.

1) Find daily-sum polarities of each day
   i. $\sum d+$: positive daily total
   ii. $\sum d-$: negative daily total

2) Count daily-number of tweets of each day (#d)

3) Find daily-average positive (μd+) and negative polarity (μd+) of each day
   i. $\mu d+= \frac{\sum d+}{\#d}$
   ii. $\mu d-= \frac{\sum d-}{\#d}$

4) Find meta-standard deviation of positive and negative polarities
   i. σ+: positive standard deviation
   ii. σ−: positive standard deviation

5) Find meta-average of positive and negative polarities
   i. μ+: positive meta average
   ii. μ−: negative meta average

6) Find daily sentiment polarity for each day
   i. $\mathrm{Pd} = \frac{(\mu d+) - (\mu +)}{\sigma +} + \frac{(\mu d-) - (\mu -)}{\sigma -}$

Figure 2. Proposed GNH-TD Calculation Algorithm.

3.4. Design of Social Media Big Data Collection Method

The proposed sentiment calculation algorithm for social media texts is intended to be used for measuring GNH for countries. On the other hand, the proposed framework which is uniquely designed for this study is not only composed of only sentiment calculation algorithm (GNH-TD) but also includes a novel social media big data collection technique which is designed to be used for Twitter platform. This method consists of three main steps. These steps are defined in the following part.

3.5. Accessing and Collecting Trend Topics (TT)

In their study, Zheng, et al. [72] discussed the location prediction methods on Twitter researches. They state that possible methods for location based studies can be as listed below:

- Accepting users' self-declared profiles for location
- Aggregating geo-tags attached with users' tweets

- Choosing the most frequent city involved in the geotags
- Choosing the first valid geotag, and convert it to an administrative region, a cell, or coordinates
- Choosing the geometric median of the geo-tags

In addition to these, due to possible privacy concerns, empty and noisy information also appear in user profiles. Therefore stating a location and accessing users (public) of that location is not a proper way. Also, if the research is about GNH calculation for a country, collecting users from Twitter who are from a specific country is not directly applicable with Twitter APIs. Similarly, although Twitter allows programs and devices to state geo-codes while publishing their tweets, the ratio of this geo-code usage is very low [73]. Due to this fact, collecting tweets and classifying them in terms of their possible geo-codes is not appropriate and efficient method. Instead, a complex but more efficient and valid method is be designed in data collection phase of proposed framework.

As it is well known, Twitter provides APIs that allow developers, researchers and practitioners to collect data relevant to their studies at no cost. Twitter allows programmers to utilize those APIs which can be classified in terms of their objectives as: (a) REST API, which is popularly used for designing web APIs to use pull strategy for data retrieval; and (b) Streaming API, which is used for continuous stream of public data with a push strategy. At this point, REST API method is advised to be used to collect data.

In order to gather a sample of active users, since it cannot be directly accessed with a single REST API, a TT search API ("GET trends/place") is suggested to be executed. This TT API works for different weeks for random sampling. Executing this API within the limit (100 APIs/h) and from each executions, gathering 10 trend topics together with their characteristics, a dataset of approximately 300 unique trend topics (hashtags) for each country are intended to be collected using their "where on Earth identifier" (woeid). The data includes the following features;

- TT name,
- TT created at,
- TT search query,
- TT URL values.

3.6. Accessing Users from TT and Filtering Bot (Automatic) Accounts

Collecting TT for a given "woeid", TT search query feature is advised to be used in "GET search /tweets" API to get 200 recent tweets about each TT. This API would help to collect tweets and unique users' features of those tweets. The following variables can be stored for each user account using the "json" format of the API.

- Account ID
- User name
- Screen name
- Number of followers
- Number of friends (followees, number of people s/he follows)
- Number of tweets
- Number of "favorited" tweets
- Account description
- Language
- Account creation time

After accessing the users and storing the account information of them, filtering phase begins. One of the most problematic issues in big data collection methodologies is detecting and filtering bot accounts (automatic—computer controlled—accounts used for publishing tweets with commercial or political purposes). In the proposed framework, eliminating the accounts (users) whose number of tweets are 2 standard deviations away from the mean of the users from that country is used to cope with this problem. Also, private accounts whose tweets cannot be collected via related APIs should be dropped from resultant dataset before the tweets collecting phase. This process is also important for ethical constraints in social media researches. Thus, filtering out private accounts is embedded to the framework.

3.7. Collecting Tweets of Chosen Users

The last phase of the social media data collection part of the framework is collecting users' tweets. Tweets of the sample users can be gathered by "GET statuses/user_timeline" API. But, since this API is limited to 100 most recent tweets, a back-iterative API which executes with "max_id" option should be applied. In this method, firstly users' last 100 tweets are collected. Then, the id of the last tweet is taken and it is given to the "GET statuses/user_timeline" API as "max_id" parameter for collecting last 100 tweets before the one whose id is this max_id. Figure 3 summarizes the social media data collection phase of proposed framework in pseudocodes.

1) Collect TTs
   i. Collect Twitter TTs of each country with GET trends/place API using "woeid"
   ii. 10 for each iteration of API

2) Collect users and filter
   i. Collect 200 recent tweets written on each TT with GET search/tweets API
   ii. Collect authors (users) of those tweets and their Twitter properties (info)
   iii. Drop the ones whose account created before the beginning of intended research period
   iv. Eliminate the ones whose language is not the language of the related country
   v. Filter out the ones whose accounts are private
   vi. Calculate the standard deviation and mean of the number of tweets of remaining users
   vii. Remove the ones whose number of tweets are 2 standard deviations away from the mean
   viii. Randomly choose the given (selected quota) number of users

3) Collect tweets of users
   i. For each user
      - If first iteration of loop
            Collect users' 100 recent tweets with GET statuses/user_timeline API
        Else
            Collect users 100 tweets before max_id with GET statuses/user_timeline API
      - Take the oldest tweets' id and set as max_id
   ii. Stop loop if last collected tweet's creation time is before beginning of intended research period
   iii. Delete tweets before beginning of intended research period

Figure 3. Social Media Data Collection Methodology.

4. Implementation and Evaluation of the Framework

4.1. Choosing Countries for Sample and Collecting Tweets

According to the official web site of the European Union (EU), www.europa.eu, the EU is a unique economic and political partnership among 28 European countries that together cover much of the continent. In addition to those 28 member countries, there are seven candidate and two potential candidates. Since the main aim of this study is to draw a happiness map of European citizens with multilingual sentiment analysis framework of Twitter data, the main criteria for choosing a country for the framework are set as follows:

- the country should be open to Twitter usage with no bans or censorship
- there should be only one national language spoken within the country and that language must exist in our sentiment analysis dictionaries.

Based on these criteria, the eleven countries are given in Table 1 and Figure 4 were chosen for the study. As it is mentioned in the data collection method, a REST API for tending topics (TT) with geocodes of those countries was executed for a period of time (three weeks to two months, depending on the countries). At the end of the TT API execution for 11 countries representative samples of users (in 1/5000 ratio with respect to populations [74]) were accessed.

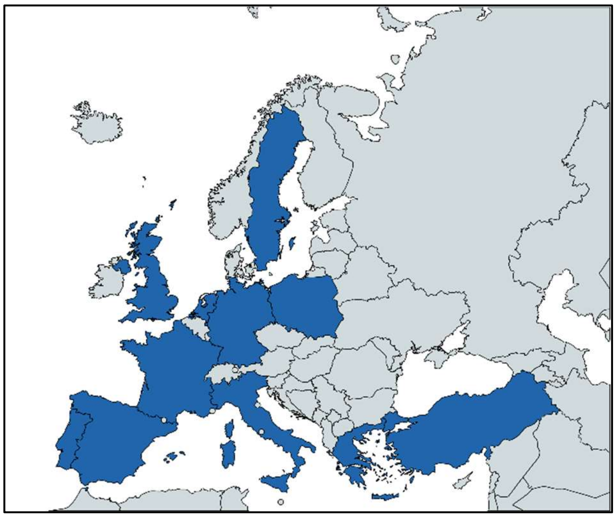

Figure 4. The Eleven European Countries chosen for the analysis.

Table 1. The ten European Countries and their main languages chosen for the analysis.

	Country	Language
1	Germany	German
2	The Netherlands	Dutch
3	France	French
4	Greece	Greek
5	Italy	Italian
6	Portugal	Portuguese
7	Sweden	Swedish
8	Poland	Polish
9	Spain	Spanish
10	Turkey	Turkish
11	United Kingdom	English

As it can be seen in Table 2, there are 38 million people in Poland in which 25 million are internet users. For the ratio of 1/5000, we should access 7644, but, while we accessed 1,161,760 users with 1669 trend topics for about two months execution of the API, only 1.139 are using Polish and created before 2010 and this number is far less than 7644 (1/5000 of the total population).

The situation was the same for Greece, so those two countries were dropped from the sample. Moreover, the ratio of the sample over the total population of the countries is (Total C/Total B) 0.02287% which can be concluded as a generalizable sample ratio. At the end, those tweets of 110,062 sample users were gathered by "GET statuses/user_timeline" API. Since this API is limited to 100 most recent tweets, a back-iterative API which executes with "max_id" option was applied as mentioned in Figure 3. This way, all the tweets of every user were collected from 1 January 2010 00:00 GMT to 31 December 2015 23:59 GMT. The yearly number of tweets per country are listed in Table 3.

Table 2. Sample Frame and Number of Accessed Users.

Country	Internet Users [75] (A)	Total Country Population [75] (B)	Number of Trend Topics Accessed	Total Accessed Users	Using National Language and Created Before 01/01/2010 (C)	Ratio to Total Population (B)/5000
Germany	71,727,551	82,652,256	1688	1,208,375	19,868	16,530
United Kingdom	57,075,826	63,489,234	789	119,335	15,856	12,698
France	55,429,382	64,641,279	3750	1,679,862	15,414	12,928
Italy	36,593,969	61,070,224	2660	1,308,952	14,487	12,214
Turkey	35,358,888	75,837,020	6189	1,075,541	17,709	15,167
Spain	35,010,273	47,066,402	1611	446,803	13,058	9413
Poland	25,666,238	38,220,543	1669	1,161,760	1139	7644
The Netherlands	16,143,879	16,802,463	288	194,570	5663	3360
Sweden	8,581,261	9,631,261	1488	1,119,278	2777	1926
Portugal	7,015,519	10,610,304	142	180,674	3370	2122
Greece	6,438,325	11,128,404	1060	792,048	721	2226
TOTAL	355,041,111	481,149,390	21,334	9,287,198	110,062	96,230

Table 3. Yearly number of tweets collected for countries.

Country	2010	2011	2012	2013	2014	2015
Germany	1,594,312	2,167,848	3,446,841	5,579,979	11,038,771	14,500,870
United Kingdom	264,460	696,529	1,987,674	4,127,235	10,243,911	26,893,481
France	442,461	976,445	2,594,032	4,762,945	9,608,994	19,044,399
Italy	430,638	1,027,982	3,371,571	5,547,187	8,791,952	14,411,831
Turkey	141,592	595,032	2,162,091	5,097,690	7,707,706	11,430,470
Spain	174,285	626,509	1,748,940	3,613,995	8,966,293	25,190,433
The Netherlands	330,863	907,171	1,543,801	2,384,925	4,686,031	7,841,054
Sweden	131,119	258,425	689,734	1,190,342	2,031,537	2,114,549
Portugal	116,946	250,063	390,444	840,847	2,372,739	6,754,129

To sum up, totally 255,842,103 tweets were collected to perform sentiment analyses for nine countries for a six year period.

4.2. Sentiment Analysis Algorithm and GNH-TD Calculation

After collecting tweets of 110,062 users from nine countries, the proposed sentiment analysis algorithms (Figures 1 and 2) were applied for all tweets. A sample tweet and analysis results are shown in Figure 5.

> Really good coverage of #ParisAttacks on itv. Clear and concise programme, but god! what an incredibly scary night. There are no words :_(

Figure 5. Sample Sentiment Analysis Report of a Tweet.

This tweet was published in United Kingdom at 13 November 2015 about the Paris terrorist attacks. The words "good" has +1 weight in dictionary, but since there is "really" near before it, the weight is increased by algorithm to +2 (booster word). The word phrase "but god" would have positive or negative feeling but in the same sentence there is "clear and concise" words (+1) thus the weight of "but god" was automatically stated as −1. And, "scary" has a weight of −2 but the booster word "incredibly" increased its negative value to −3. Lastly, the emotion :_(has the polarity of −1 in the emoticon dictionary. At a result, the polarity of the tweet stated as +3 and −5. By this methodology all the tweets of the users were calculated and their polarities were stored into database.

Then with the GNH-TD algorithm (Figure 2) daily GNH values of all countries were calculated (for 2191 days–6 years).

5. Analysis

The main aim of this study is to state a framework for GNH calculation via social media big data. Thus, proper number of active users and their tweets are calculated with proposed data collection method. Afterwards, the novel sentiment calculation algorithm was applied to more than 250 million tweets. On the other hand, before stating the GNH values of the countries, the validity and reliability of the results and algorithm should be examined. In this perspective, first three research questions were asked and analyzed. The first question is "Is there face validity when the polarities determined by sentiment analysis framework are compared with Stock Market Index and Exchange Rates?" To check face validity of the results, the historical data (from 1 January 2010 to 31 December 2015) of main stock market indices of the countries were collected from Yahoo Finance web site (https://finance.yahoo.com/). Also, Euro-Dollar (eur-usd), Euro-Pound (eur-gbp) and Pound-Dollar (gbp-usd) daily exchanges are collected. Then, bivariate correlations between the daily GNH-TD results, main stock indices and monetary exchanges are examined with Pearson's Correlation statistical analysis. The results shown in Table 4.

Table 4. Results of Face Validity Pearson's Correlation Analysis.

		GNH-TD National Market Index	GNH-TD EUR-USD	GNH-TD GBP-USD	GNH-TD GBP-EUR
Germany DAX	Pearson Correlation	−0.731 **	0.498 **	0.059 *	0.589 **
	Sig. (2-tailed)	0	0	0.019	0
	n	1527	1565	1565	1565
United Kingdom FTSE100	Pearson Correlation	−0.603 **	0.627 **	0.124 **	0.714 **
	Sig. (2-tailed)	0	0	0	0
	n	1514	1565	1565	1565
France CAC40	Pearson Correlation	−0.537 **	0.494 **	0.079 **	0.572 **
	Sig. (2-tailed)	0	0	0.002	0
	n	1537	1565	1565	1565
Italy FTSEMIB	Pearson Correlation	−0.183 **	0.417 **	−0.044	0.545 **
	Sig. (2-tailed)	0	0	0.081	0
	n	1538	1565	1565	1565
Turkey BIST100	Pearson Correlation	−0.548 **	0.506 **	−0.004	0.631 **
	Sig. (2-tailed)	0	0	0.888	0
	n	1511	1565	1565	1565
Spain IBEX35	Pearson Correlation	−0.268 **	0.503 **	0.054 *	0.597 **
	Sig. (2-tailed)	0	0	0.033	0
	n	1535	1565	1565	1565
The Netherlands AEX	Pearson Correlation	−0.687 **	0.551 **	0.184 **	0.584 **
	Sig. (2-tailed)	0	0	0	0
	n	1537	1565	1565	1565
Sweden OMX30	Pearson Correlation	−0.641 **	0.469 **	0.056 *	0.551 **
	Sig. (2-tailed)	0	0	0.026	0
	n	1506	1565	1565	1565
Portugal PSI20	Pearson Correlation	0.344 **	0.585 **	0.118 **	0.664 **
	Sig. (2-tailed)	0	0	0	0
	n	1440	1565	1565	1565

** Correlation is significant at the 0.01 level (2-tailed); * Correlation is significant at the 0.05 level (2-tailed).

Results showed that all the GNH-TD of countries are significantly correlated with monetary exchanges and stock market indices. The second research question is about convergent validity of the proposed framework: "Is there convergent validity when the GNH results of the sentiment analysis framework and GNH survey results of Organization for Economic Cooperation and Development

(OECD) report are compared?" To check this validity, OECD life satisfaction survey results of all countries were gathered from OECD Data Bank (http://stats.oecd.org). Since there are online four year results (2012 to 2015) matching to our time interval, only 36 GNH measures (4 years × 9 countries) were examined again with Pearson's Correlation Analysis. Results of this analysis shown in Table 5.

Table 5. Convergent Validity Analysis Results.

		OECD-Better Life Index	GNH-TD
OECD-Better Life Index	Pearson Correlation	1	0.854 **
	Sig. (2-tailed)		0.000
	n	36	36
GNH-TD	Pearson Correlation	0.854 **	1
	Sig. (2-tailed)	0.000	
	n	36	36

** Correlation is significant at the 0.01 level (2-tailed).

Since there is a significant and high correlation between the GNH-TD results and OECD survey report, the convergent validity of the proposed framework is proved. Additionally, this result can be concluded as a replacement of this social media sentiment analysis framework to the OECD survey method for life satisfaction analysis among countries. The third research question is about reliability of the dataset and results: "Is there data reliability when the peaks/troughs of the graphs of sentiment analysis framework are compared with specific dates obtained from news archives?" The common way for finding reliability of the sentiment analysis in literature is that the results are compared with findings from other sources such as news, archives, questionnaires, company secondary data, even manual provided and classified data, etc., but by this backward accuracy checking method, the real power of sentiment analysis cannot be detected. In other words, we cannot claim that our sentiment analysis results are accurate when we check the results with real data, because in this way we probably miss some real events to check. Therefore, a forward methodology for our accuracy check is more appropriate and valuable. In this forward method, first the data from the past are collected and the socially effective days of the countries for the selected time period were stated. For stating those days, the Wikipedia events pages were used (e.g., 2014 in Spain https://en.wiki.ng/wiki/2014_in_Spain, 2011 in Turkey https://en.wiki.ng/wiki/2011_in_Turkey). Then the results of the sentiment analysis are checked with this data in terms of how much of the past could be detected. In country level, the reliability of sentiment analysis framework was checked in terms of detecting those effective days. Since there are 2192 days in the chosen time interval and since GNH-TD found an aggregate happiness polarity value for all of those days, a threshold value was needed for determining the socially important days where after would be called as "extraordinary" days. To this respect, threshold value was calculated as "two standard deviations away from mean". The mean and standard deviation values of all the polarities of 2192 days and Positive and Negative Threshold values for all countries are listed in Table 6.

After examining deeply the days of having negative aggregate polarities below negative threshold or upper positive threshold values, the detection accuracy of the proposed sentiment analysis framework is listed in Table 7.

To sum up, since all the accuracy percentages are bigger than 70% threshold value [76], the reliability of the dataset and proposed GNH-TD framework is proved.

Table 6. Mean and Standard Deviation of Polarities and Threshold Values.

Country	Mean (Negative)	Standard Deviation (Negative)	Negative Threshold	Mean (Positive)	Standard Deviation (Positive)	Positive Threshold
Germany	−1.2192	0.6364	<−2.492	1.3684	0.6307	>2.6298
United Kingdom	−1.4522	0.8271	<−3.1064	1.5253	0.7507	>3.0267
France	−1.4936	0.8214	<−3.1364	1.2965	0.5799	>2.4563
Italy	−1.1926	0.549	<−2.2906	1.2906	0.5678	>2.4262
Turkey	−1.1579	0.5092	<−2.1763	1.2656	0.5526	>2.3708
Spain	−1.4155	0.79	<−2.9955	1.6825	0.9871	>3.6567
The Netherlands	−1.3444	0.6957	<−2.7358	1.2974	0.613	>2.5234
Sweden	−1.2122	0.5478	<−2.3078	1.293	0.5725	>2.438
Portugal	−1.3959	0.7635	<−2.9229	1.3422	0.6323	>2.6068

Table 7. Detection Accuracy Results.

Country	Number of Event Days in Wikipedia Pages	Number of Matching Days from GNH-TD	Detection Accuracy
Germany	105	74	70.48%
United Kingdom	121	104	85.95%
France	137	112	81.75%
Italy	112	83	74.11%
Turkey	163	146	89.57%
Spain	72	52	72.22%
The Netherlands	84	59	70.24%
Sweden	69	57	82.61%
Portugal	58	42	72.41%

6. Results

The fourth and last research question of the study is about the GNH results of countries for chosen 6 year period: “What are the GNH polarities of European countries in accordance with the proposed Twitter sentiment analysis framework?” In order to answer this question, first of all, the yearly (average) results of the countries are found as in Table 8.

Table 8. Yearly Average GNH-TD of Countries for 6 years period.

Country	Average Sentiment Polarity
Germany	0.040165
Sweden	0.040715
France	0.050131
The Netherlands	0.055155
Italy	0.058553
Spain	0.085874
United Kingdom	0.104333
Turkey	0.105635
Portugal	0.132342

If these results are put in to a gradient color scale from Red (meaning unhappiest) to Green (meaning happiest), the resultant picture (Gradient Color GNH Map of Europe) would be as in Figure 6.

But, this kind of aggregate figures are usually misleading. For avoiding this kind of ambiguous perspective, a detailed and comparable diagram should be designed. In Figure 7, yearly GNH-TD values for all countries are drawn.

This chart shows more detailed results some which can be listed as:

- A negativity trend appears in social media happiness of all countries through the six years period. This result is also approved by OECD Life Satisfaction results of countries, because those values are decreasing also year by year.
- France has changed its positive happiest level from 3rd unhappiest through six years.
- One of the most impressive results of the study, while Turkey starts with second highest (happiest) position in 2010 and in the second position in aggregate results (Table 8); it is the unhappiest country among all at the end of 2015.

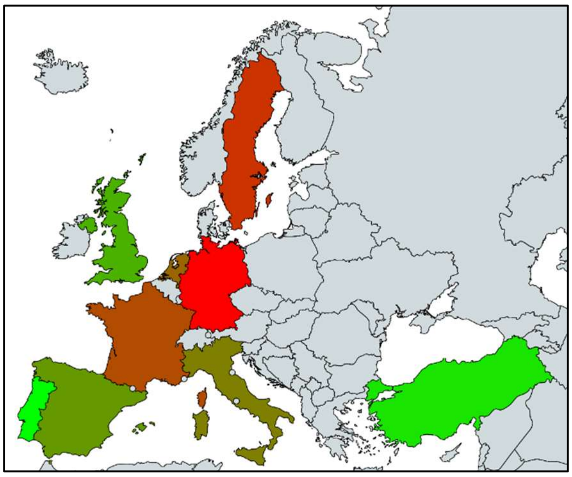

Figure 6. Gradient Color Map of GNH for 9 European Countries between 2010 and 2015 (Red-Unhappy...Green-Happy).

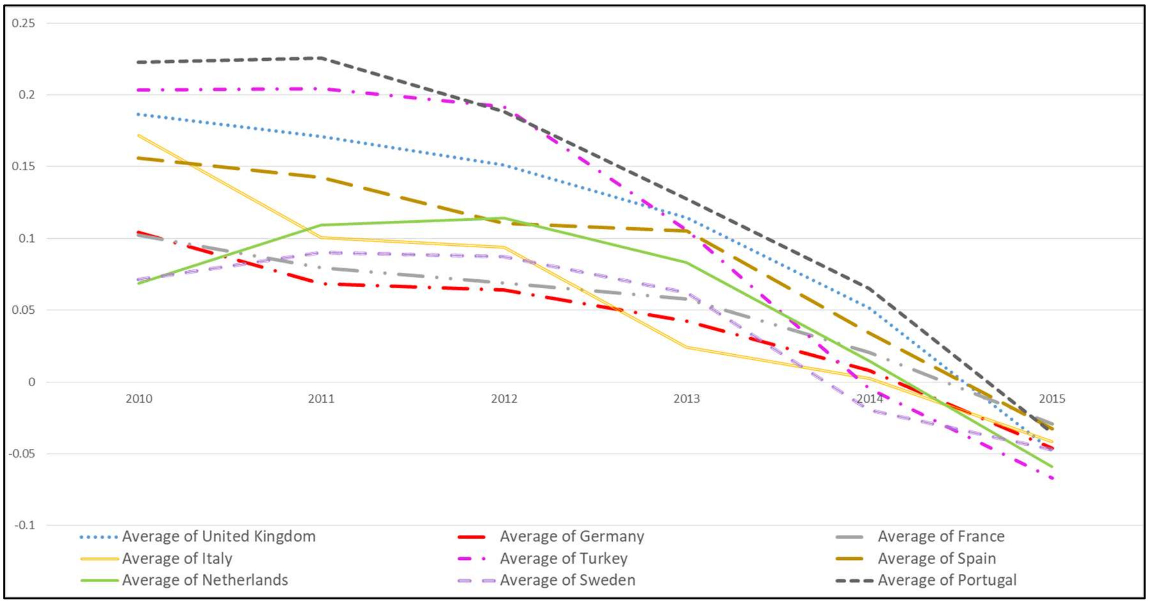

Figure 7. Yearly Average GNH values of Countries.

6.1. EU Countries Daily Sentiment Analysis

Before analyzing the countries one by one, in order to see the big picture of EU countries the total European daily sentiment results are determined as shown in Figure 8.

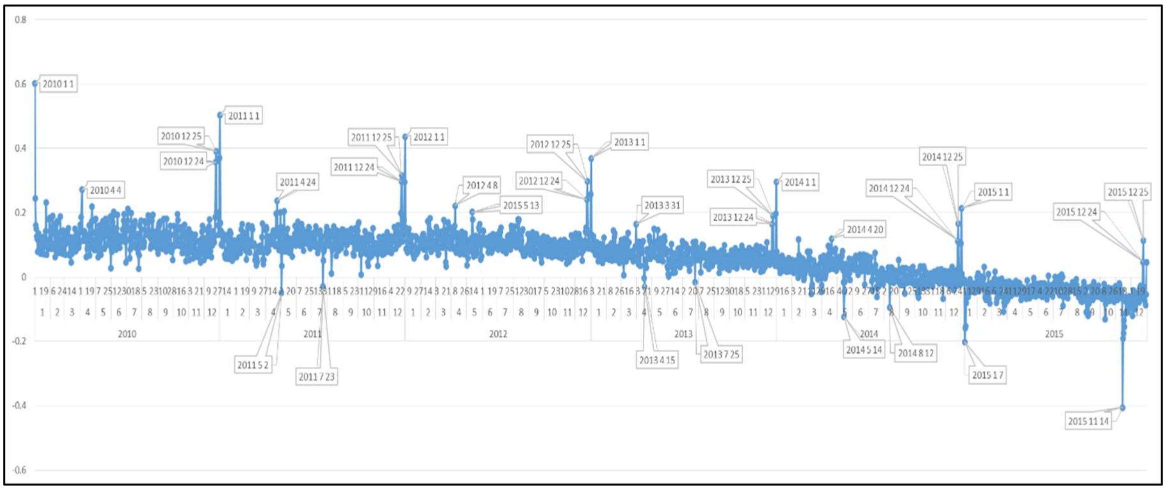

Figure 8. Daily Sentiment Polarities of EU Countries from 2010 to 2015.

At first glance, a steady smooth trend appears from 2010 to the end of 2012 where afterwards a negative tendency arises. When positive peaks of sentiment dates are considered, it is seen that the positive peaks are realized in Christmas Eve (24 December), Christmas Day (25 December) and New Year's First Day (1 January) for all years. The second positivity repeating event days (for all years) are Easter Days (4 April 2010, 24 April 2011, 8 April 2012, 31 March 2013, 20 April 2014) as an ordinary fact. But, since 2015 can be called as terrorism year which surrounded all the Europe, no Easter celebration appears in the Graph in 2015 April while it is a common fact for all other years. Lastly, a positive peak is shown in 13 May 2012 which is Mother's Day.

Terrorist attacks and events have a dominance on the graph when the negative sentiment dates are analyzed. For instance, the most negative sentiment of Europe is 14 November 2015 in which terrorist attacks occurred in Paris (causing 137 deaths). Similarly, the Charlie Hebdo assault (7 January 2015) and Workers' Youth League (AUF)-run summer camp terrorist attack (23 July 2011) are other negative sentiment days. 15 April 2013 is an interesting negative day; in this day there is not any negative event in Europe but a terrorist attack occurred in Boston Marathon in which there were lots of European participants (audiences and marathoners). Also, big accidental disasters (Soma mine explosion in Turkey on 14 May 2014 and train accident in Spain on 25 July 2013) appeared in the graph as most negative days. On the other hand, 12 August 2014 is also one of the unhappiest days as can be seen from the graph. On this day the UEFA Super Cup final match was played between Real Madrid (the most popular club of Spain) and Sevilla (the oldest club of Spain) and Real defeated Sevilla (2-0). It seems that in Europe football fans did not like the victory of Real Madrid. Lastly, 2 May 2011, as another negative day, is the day Osama Bin Laden died. At first glance, this day might be thought to be a positive day for Europe, but the tweets showed that it was a remembrance day for the thousands of innocents killed in the 9.11 event.

After the general analysis of Europe, the country datasets are graphed (Appendix A) and examined specifically for stating country specific negative and positive peak dates. Findings, discussed in following sections, show that the algorithm is also successful for capturing the country-based social events as it is for EU countries in common.

6.2. Daily Sentiment Analysis for Germany

When the German dataset is investigated, 13 July 2014 when the German national football team became world champion in Brazil is found to be one of the happiest days. Also, as a common fact, Saint Valentine's Day (14 February) appears as one of the happiest days in the scale for all years. When we examine the negative days, interesting results are found. Firstly, as the unhappiest day of 2010, in 24 July, a massive stampede at the 2010 Love Parade in Duisburg killed 21 people and injured dozens (at least 500) more people. This Love Parade disaster affected German society very much and obviously led to a high position in GNH-TD results. Additionally, there are two nearly same degree negative days in 2011. In 27 March 2011, state elections were held in the Baden-Württemberg and Rhineland-Palatinate states. The negativity of the day was due to the fact that while Angela Merkel's Christian Democrats had 39% and positioned the first, the total of Greens and Social Democrats became more than 40%, thus this result was concluded as "loss of Merkel".

6.3. Daily Sentiment Analysis for Sweden

The first interesting finding from the Sweden dataset is that Swedish society does not react extraordinarily in social media and there is a smooth waving in their sentiment dataset. They don't react to 1 January as much as other EU countries and even their national day (6 June) does not appear as extraordinarily positive in the scale when compared to other days. This emotionlessness for National Day of the country is very common for this country. It is a well-known fact that in 2004, the Swedish parliament started the discussions for making this day a public holiday in order to make society more interested in celebrating this day, but even the duration to end up with the decision for making it a public holiday took about one year. But the Midsummer Eve is an extraordinary social event (positive) for this country (e.g., 21 June 2013). As the general happiness tendency analysis, Swedish people has the happiest year in 2012 different from other countries. The negative extraordinary days' analysis, as expected, showed that Paris attacks in 14 November 2015 has the most negative position in this country too. But, the negativity of 22 July 2011 is more than 4 November 2015 in Sweden where 22 July 2011 is the day of Norway terrorist attacks, and the reason of this high reaction may possibly be due to being a neighbor country of Norway is. As a result, it can be stated that, in Sweden terrorist attacks in Europe have negative effect on society while there is not widely peak positive days such as national days, religious events or sport events in society.

6.4. Daily Sentiment Analysis for France

Daily GNH values of France showed that French people have a big tendency to celebrate New Year in 1 January. It is interesting that French people do not focus on Christmas (24 December) as much as others. This fact shows that in France, 1 January has a meaning of New Year than Christmas. On the other hand, extraordinary positivity of 23 May 2010 showed a celebration of Whit Sunday. Also, 27 March 2011 is the Cantonal Election day in France and it seems the results gladden French people. The negative extraordinary days' analysis for France show that Paris attacks (4 November 2015) and Charlie Hebdo shooting (7 January 2015) are the unhappiest day of the six year period. Another negative date is in 21 March 2012 where a bombing attack occurred in front of the Indonesian Embassy in Paris after president Sarkozy declares the operation done to arrest the author of the Toulouse murders. To sum up, it is very normal to find out that French society was very unhappy in 2015.

6.5. Daily Sentiment Analysis for The Netherlands

The Netherlands' sentiment polarities state that 2012 is the happiest year for The Netherlands like Sweden, though a negative tendency of happiness in the six year period. The first negative day period in The Netherlands was clearly on 24 February 2010 on which Queen Beatrix accepted the resignation of the Labor Party minister. On the other hand in the June and August periods a new cabinet formation conversations were being done and positive and negative polarity days occurred depending on the direction of the discussions. On the other hand, in 12 July 2010 there was a negative polarity, and the reason for it was the World Cup defeat of Holland national football team by the Spanish team.

6.6. Daily Sentiment Analysis for Italy

While most of the other countries showed an increase in negativity in 2012, in this country negative flow GNH-TD is smooth for the six year period. On the other hand, while peaks of positive days appear in 2010 in high amount, these peaks immediately disappear after 2011. This can be an indicator for a rapid decrease of happiness in the Italy Report between 2012 and 2016 [77]. Another interesting finding for positive polarities is that, contrary to other EU countries, Italian citizens celebrate Christmas (25 December) instead of New Year (1 January). The negativity on 19 May 2012 is because of Brindisi school bomb event which affected Italian society, who are not very familiar with terrorist attacks as other European countries, very much. At the same time the negative days show that, for all other terrorist attacks, Italy acts alike other European countries and feels unhappy.

6.7. Daily Sentiment Analysis for Spain

In Spain, of course contrary to The Netherlands, in 12 July 2010, the national football team's victory against The Netherlands shows a positive peak. The negative days of Spain in the chosen time period is surprising since while 14 November 2015 terrorism event has a negative effect on the society the, other terrorist attacks in Europe do not indicate negativism. On the other hand, on 25 July 2013 on which the biggest train accident happened and dozens were killed is one of the negative peaks in Spain.

6.8. Daily Sentiment Analysis for United Kingdom

As still a part of the EU, United Kingdom society showed positive polarities on the Christmas and New Year celebrations, too. All other positive days are about football matches which support the belief about the football focus of this society. When the negative days are analyzed, the unhappiest day of all time interval is 14 November 2015, showing a big abhorrence to terrorism. On the other hand, like happiest days, most of other unhappiest days (e.g., 12 August 2014) are related to football events. Moreover, of course, 9 August 2011, as a domestic negative day, London riots and street fights appeared as one of the unhappiest days of 2011.

6.9. Daily Sentiment Analysis for Turkey

Turkey is the only country that was chosen from the candidate countries pool of the EU. However, the results of this country show the differences of EU citizenship. The positive GNH-TD days of Turkey is very different from the other EU countries. For instance, Turkish society does not celebrate New Year as a peak happy day of the year. Celebrating Christmas was not expected from this Muslim country but they use Gregorian calendar and New Year celebration would not be surprising. However, 15 November 2010 is a religious ceremony in İslamic World (Kurban) and 19 August 2012 has another ceremony (Ramadan); and these days have positive peaks. 30 August 2011 is Turkish national victory day and the positivity of this local celebration day is again natural. The difference of Turkish society from EU countries is seen better in the negativity analysis of Turkish tweets. While 14 November 2015 is the unhappiest day for all other countries, it is not the unhappiest day in Turkey. Turkey has its own peak on 10 October 2015, where there was a terrific terrorist attack in capital city of Turkey (Ankara) resulting with more than 100 deaths and which was not too much considered as negative day by other EU countries. 14 May 2014 was the black day for Turkish citizens because of mine explosion in Soma with more than 200 deaths.

6.10. Daily Sentiment Analysis for Portugal

When the Portugal dataset is analyzed, positive polarities are seen on 10 to 12 June of the years which are about Portugal Day celebrations. The negative polarities shows that as another EU country, Portugal shares the sadness of terrorist attacks. However, the results have a tremendous trough date (3 May 2011) for this country, on which Portugal has reached an agreement with EU and IMF on 78 billion Euro financial rescue package, becoming the third Eurozone country to be bailed out of a sovereign debt crisis. This finding shows that economy is still one of the main factors of GNH for societies.

7. Discussion and Conclusions

This social media big data analysis study is about learning from the past in country levels and detecting exploratory findings in multicultural and multilingual levels. With this perspective, a novel social media big data sentiment analysis framework, which consists of data collection, filtering, sampling and sentiment analysis algorithm, was conducted. In this respect, 11 countries have been chosen from Europe for Gross National Happiness Analysis with Twitter data. After filtering, more than 110,000 active users from nine countries were accessed and their tweets from 1 January 2010 to 31 December 2015 were collected. After validating the algorithm results with convergent and face validity analysis, reliability of the data was checked. Lastly, with this functioning algorithm, GNH results are discussed in general and on country domains. Investigating the results deeply, terrorist attacks and disasters (air crashes etc.) have naturally negative effects on society soul. Also, in Europe countries, society is effected by terrorist attacks not only in their country but also in other countries. This result concludes that in (especially for negative dates) extraordinary situations, there still exists a "European Citizenship" concept. Also, a negative sentiment tendency for all countries has approved over 6 year period, unfortunately. When the proposed social media sentiment analysis framework is compared to alternative approaches, this framework can be found conspicuous with following newly designed features:

- This framework does not only include sentiment analysis algorithm but also contains data collection, sampling and filtering methodology which are the main challenges of big data analysis [78,79].
- The usability of the proposed framework meets a deficit, tested and validated for multiple languages, which was declared as future study recommendations of several studies [79–82].
- In addition to accessing the threshold value (70%) stated in [76], some of the accuracy of the stated framework results are more than the results of [83] (~75%) which high accuracy of machine learning method and results of [84] (80%) in which feature- and decision-level fusion methods are used.
- Lastly, it can be stated that comparing to the survey based methodology of GNH calculation by the global institutions (e.g., OECD), time series results (daily, monthly etc.) can be drawn and explained with this proposed framework. Thus this promising framework can contribute the researchers for related specific social psychology studies.

8. Future Study Recommendations

The main contribution of this study is that it is possible to find out societies' total feelings in daily (even hourly) levels via social media big data analysis. For future studies, it can be recommended that the daily and hourly results of the algorithm might be analyzed in a deeper way with the help of social psychologists in terms of socio-cultural effects. Also, in order to enlarge the scope of cross-cultural analysis, most frequently used words, idioms and emoticons can be examined to detect exploratory differences of societies. Lastly, as known, machine translation of tweets for sentiment analysis is an alternative methodology for multi-lingual sentiment analysis [85]. Thus, as future study, the framework of this study can be integrated with machine translation methodology to determine GNH of countries on a common language.

Author Contributions: This manuscript was made on the process of PhD study. M.C., as a student, was supervised by M.O. during the process. M.C. conceived and designed the framework and performed the data collection. M.C. and M.O. analyzed and discussed the data. M.C. implemented the algorithm and stated the results. M.O. and M.C. wrote the manuscript. M.O. provided relevant information and instructions during the whole progress. All authors have read and approved the final manuscript.

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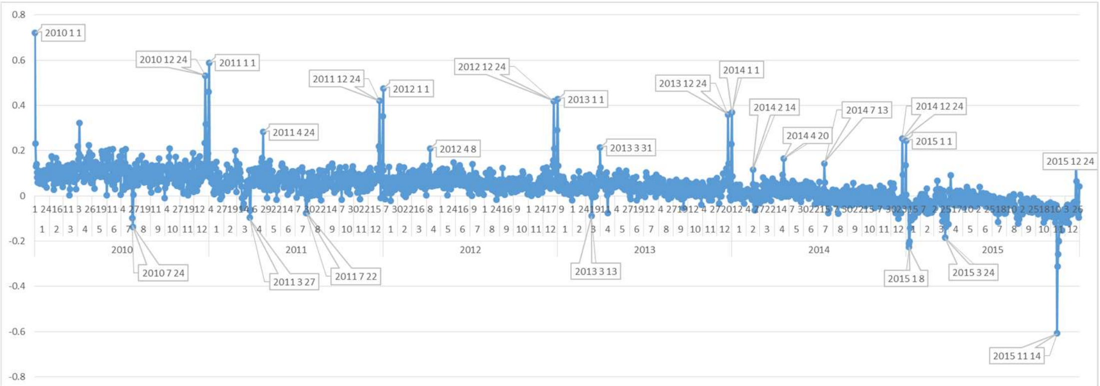
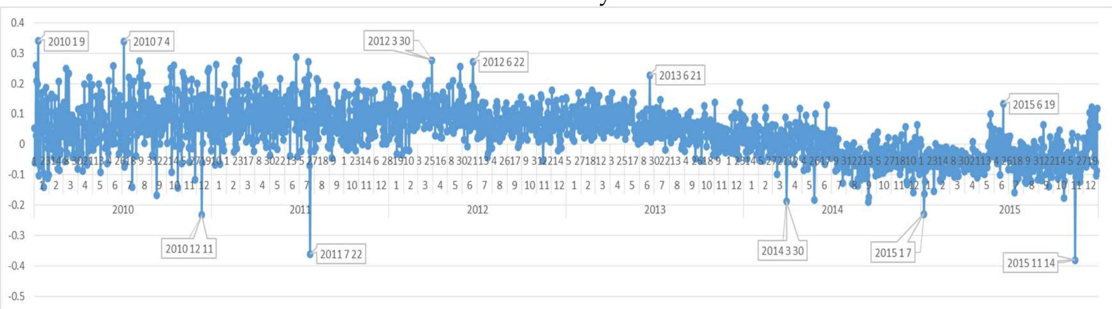
Conflicts of Interest: The authors declare no conflict of interest.

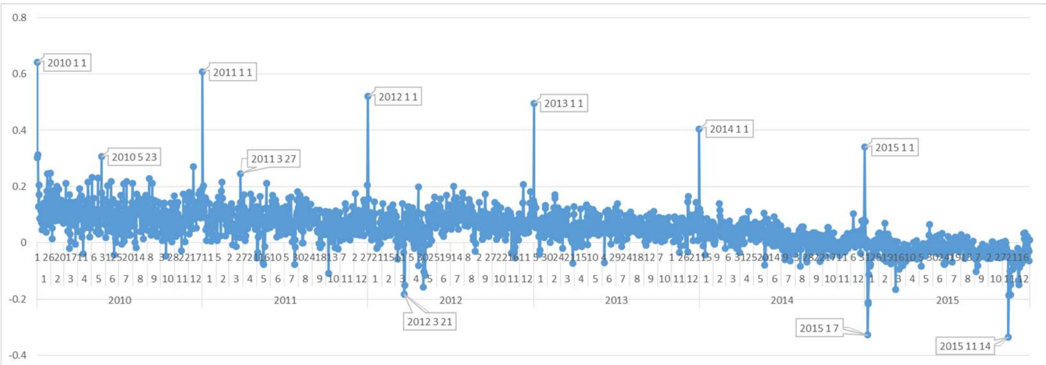
Appendix A. Daily Sentiment Polarity Graphs of Countries



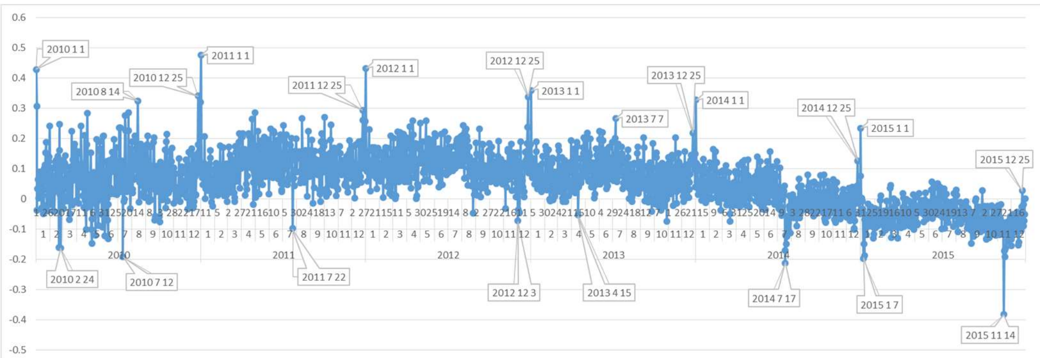
Germany



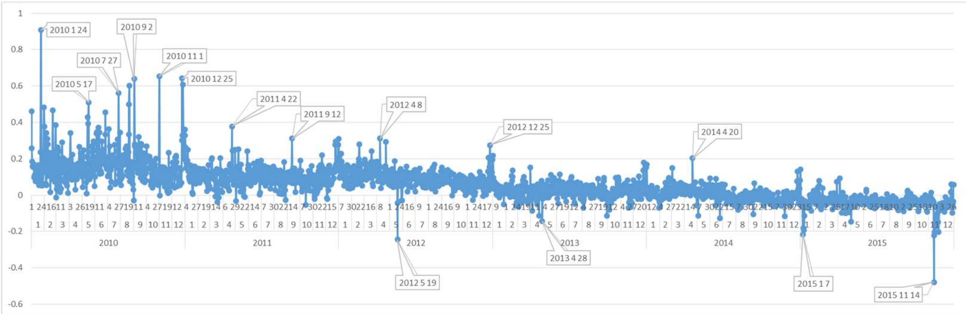
Sweden



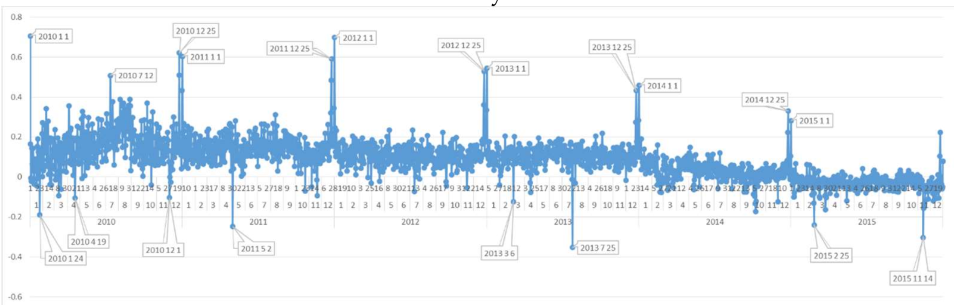
France



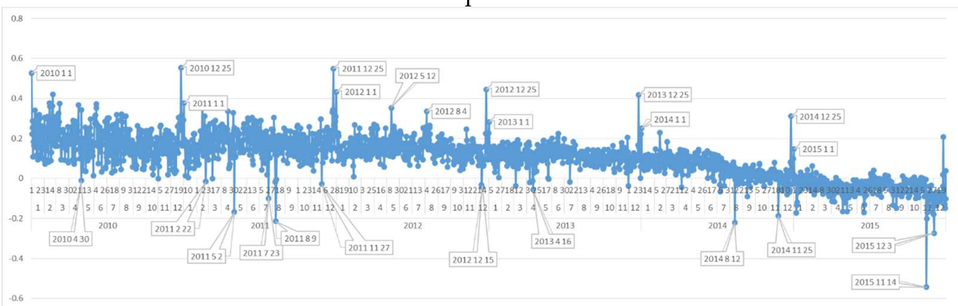
Netherlands



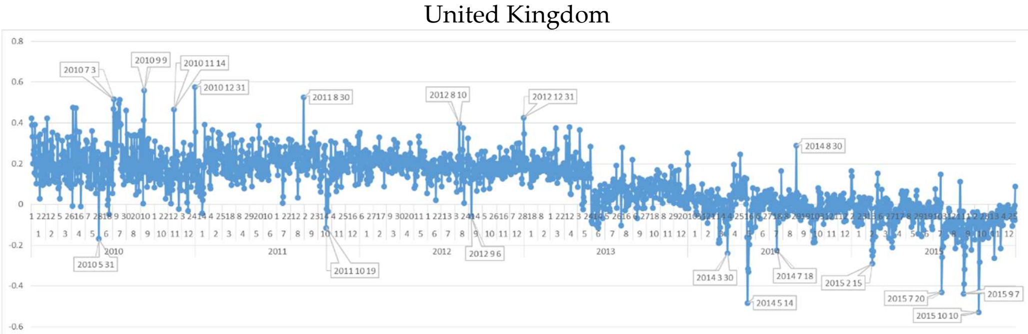
Italy



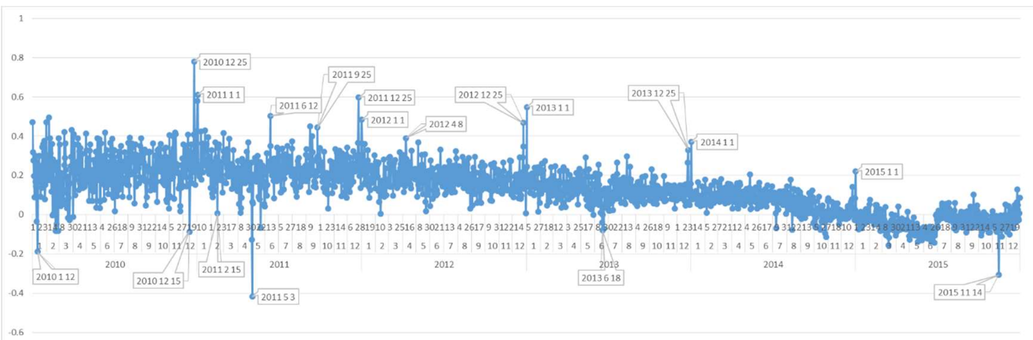
Spain



United Kingdom



Turkey



Portugal

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