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Social Media Trends and Prediction of Subjective Well-Being: A Literature Review

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Abstract

Everybody is now addicted to the online social media. Social media sites have been used by millions of people globally. Each individual expresses his thoughts, daily life events and opinions on social media. The individuals' expressions on social media are mostly in the text form. The text contains sentiments, opinions, attitudes and emotions of the individuals, which are largely related to the happiness in the personal life of individuals. Extensive usage of social media affects the happiness, which can be either on the positive or negative level. Happiness level is normally measured by self-report and often been indirectly characterized by more readily quantifiable economic indicators such as Gross Development Product (GDP) or Genuine Progress Indicator (GPI). However, the growing importance of linguistic text analysis of social media gives a direction to predict the happiness of individuals and is termed as Subjective Well-Being (SWB). SWB is the scientific term used to describe happiness and quality of life of individuals. It includes emotional reactions and cognitive judgments and is of great use to public policy makers as well as economic, sociological and psychological research. The richness and availability of social media make it an ideal platform to conduct psychological research in the topic SWB. In this paper at first, the evidence of the importance of the social media analytics has been provided followed by identification of major factors involved in SWB. Further the effects of social media usage on the SWB of individuals has been elaborated.

Keywords: *Well-being, Happiness, Social media, Social well-being, Subjective well-being, Social networking, Social happiness, Literature review*

1. Introduction

The advancement of big data tools and techniques in a short time has reduced the many problems of large data stored on cloud servers. Huge data stored on servers mostly come from web services, such as blogs, social media sites, forums etc. Social media is a combination of two words, the first part Social refers to the interaction between people by sharing information to and fro, and the later part Media refers to a medium of communication, like the internet. Social media can be defined as forms of electronic communication (as Web sites for social networking and microblogging) through which users create online communities to share information, ideas, personal messages, and other content (as videos) [1]. The internet, mobile technologies, and Internet of Things (IoT) drastically diffuse the social media. It is the array of web-based applications which define the way social media operates. Examples include social networking, microblogs, weblogs, online forums, podcasts, and 3-D virtual reality.

Social media word is used vaguely, every website has been considered as social media.

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Many popular websites dedicated to social media are Twitter (social networking and microblogging), Facebook and Google+ (social networking), YouTube and Netflix (media content sharing), Blog and Blogger (web blogging), MozVR and Second Life (virtual reality). Social media websites generally contain heterogeneous data, like text, pictures, videos, etc. Facebook is the first social media website to cross the 1 billion mark of registered user (January 2016), Face- book had 1.55 billion active users [23]. The Ice Bucket Challenge [4] on Facebook in 2014 was the one of the biggest trends, ALS.net raised $4 million and every penny was spent on research. The attraction of people to these types of trends, quickly adoption and spreading it to others on social media, has been possible because of the big data is handling the background processes on servers. Social media attracted every age group, mainly teens. Teens spend 9 hours [5] daily on social media, which have both positive and negative impact on the personal life.

Social media gain widespread adoption and become part of the ecosystem, attracting users, consumers, businesses, governments and non-profit organizations. People have been able to communicate with local and outside the country at the same time. People have leveraged the social media in smart ways, like the formation of online communities that allowed them to get moral support, education, latest information, and even promote and sell products. Similar way the impact of social media changed the whole view and promises to accelerate innovation, cost-saving mechanisms and strengthens the brand value of industries. Every company is using the social media to hype new products and services and also monitor what people are saying about the product. Firms' performance with respect to business networks can be analyzed to predict the price movement in stock market [26]. As social media applications continue to unleash a large amount of data, individuals and organizations need to transform information into decision-making intelligence and also to measure the value of their business with social media analytics.

2. Social media analytics

Social media analytics can be described as the process of collecting data from the social media websites and analyzing that data to make business decisions. Social media analytics is mostly used to mine customer sentiment in order to support marketing and customer service activities. Data analytics can be real-time or offline analysis, including factors such as influence, reach, and relevance of suitable measurements. Time considerations are important to understanding the context of data being analyzed. The importance of social media analytics can be seen as the researchers at AT&T developed advanced analytics software used to eavesdrop on customers via Twitter to find the complaints about network problems, so that users can be prioritized by extracting time and location of user's tweet through Twitter data analytics. According to this priority, the crews will be sent to fix the problems [10]. Organization's dedication to serving the mass with this level of priority makes it more interesting and creates competition among the organization. Organizations have been focusing on research and innovation in analytics based on the resources they already possess.

2.1. Offline social media analytics

Offline data analytics refers to the passive analysis of data, which is generally used for

[2] Social Media Definition," Merriam-Webster"
[3] http://www.statista.com/statistics/272014/global-social-networks-ranked-by- number-of-users
[4] https://www.als.net/icebucketchallenge/
[5] http://edition.cnn.com/2015/11/03/health/teens-tweens-media-screen-use-report/

digital marketing channels. The offline data is the specific data captured, which is generated by the user or from offline sources such as CRM data files. The captured offline data of a particular user from social media have been very useful and the outcomes of the data analysis shed light to the uncovered variables. The importance of offline analytics can be seen as the biggest presidential elections occurs in the USA, were candidates mostly campaign through social media. An attempt has been made through social media analytics [24], which proposed a reliable forecasting system of US presidential elections and US house race. The researchers present a new model, named Competitive Vector Auto Regression (CVAR). CVAR compares the popularity of multiple competing candidates by combining visual information with textual information from the Flicker social media. The proposed system accurately predicts election outcome, generalize the sentiments of the candidate photo shared and account for the sentiments of viewer comments towards the candidates. This type of system can provide campaign insights to the candidate so that candidate can work on their weaknesses and can further improve their self.

Apart from the elections, the next concerned thing is the stock market value of the country. The stock market determines the economic value of the country, many people daily share ups and downs of stock market prices on social media. Researchers suggested that stock market price movements can be predicted through social media analytics by proposing an Energy Cascade Model (ECM) [25]. ECM can effectively predict middle-term directional stock market price movements, achieving an average accuracy of 67.7 % for upward stock price movements. The ECM model can be used to more effectively analyze and predict the performance of targeted firms from automatically mined business networks. A similar approach [18] was used to explore the two major events of stock market price change and trade volume. Trust information extracted from the Twitter group was compared with Dow Jones Industrial Average (DJIA). By keeping trust information into account, the results show that price change and trade volume are more related than just counting the number of tweets and trade volume is stronger correlated than price change.

Yet another analysis has been carried out through the public micro-blogging social networking site Twitter. The performance and psychological well-being of runners [9] had been tracked, by monitoring Twitter tweets of runners group. The 925,825 messages of runners who used Nike+ fitness tracking device were analyzed. Researchers found that 1) fitness devices were most popular in North America 2) less than 2% runners consistently ran for at least 150 minutes a week, which is recommended by Centers for Disease Control and Prevention 3) physical activity lowered on Friday as the users may need to be relaxed. The runners have been recorded for 3 months long; this somehow indicates that the old records can be used for the analytics purposes. But it may be a big challenge to convert the records into some useful form before analysis.

From the language and history perspective, digitization of more than 15 million historical books and an analysis of the past 200 hundred years had been done by the tech giant Google [6], showing a change of language usage, dynamics of fame, censorship, and time compression of collective memory. The mysteries of social media before the Internet age can be solved through more efforts in this field. The large offline data analytics sometimes easier to perform because data and noise present in the data are consistent. The large volume and high velocity of data can be a real challenge, and many researchers have done marvelous work in the real-time social media analytics.

[6] http://books.google.com/googlebooks/library/index.html

2.2. Real-time social media analytics

Real-Time analytics denotes the capacity to use all available data and resources when needed. The analysis of data is carried out dynamically and reports are generated with no delay. Mostly real-time analytics is used for geographic location and tracking purposes. Nowadays, people instantly share on social media about situations like natural disasters; hence the real-time analytics of social media may provide life-saving information. Real-time social media analytics of streams and graphs called as Milano Design Week (MSW13) [1], it recommends venues to visitors of geo and temporally bounded city scale events in Milan featured 681 venues for hosting 1,127 events attended by 500,000 visitors in one week. By combining deductive and inductive stream reasoning techniques, this system analyzes Twitter's tweets and Foursquare checked ins to produce high-quality link predictions. As mentioned earlier, people spend more time on social media and share whatever is happening in the surrounding, whether it is an earthquake, car accident, tsunami or landslide.

A multi-level content analysis of Twitter tweets collected about landfall suggests that actionable information was easier to find when searching along hash- tags. The use of Twitter in pre-crisis stages of a weather event can be beneficial for the emergency management agencies [13]. Another example of real-time social media analytics is the monitoring of flu outbreaks through the proxy of user’s search. Googles Flu Trends and Dengue Trends provides estimates of flu and dengue based on search patterns [7]. Also, Google Trends [8] can accurately predict the box office success based on the rating of online mentions of individual movies and the count of the search made on YouTube. From the above studies, few things are concerned, such as the reactions of the people to the situation. The behavior of peoples varies according to the situation, which can decide that on whom they will trust blindly or may take the risk to trust others.

A rigorous and quantitative meta-analysis was conducted to investigate the empirical evidence of the most influential factors, trust, and risk which affect the individual behavior toward social media platforms [21]. The findings suggested that both risk and trust had significant effects, but trust had a stronger effect. The effects of risk and trust have been clearly visible on the social media. Trust is closely related to the happiness of the human behavior and mostly happier persons are more trustworthy.

At a growth rate of '8%, internet users are now more than 40% of entire world population. Social media continuously playing a great role to reach that mark and has touched the many aspects of human life. With this, the social media is responsible for a radical new trend that is of interest to various organizations for finding emerging and unique trends in human behavior.

3. Human behavior

Human living style, languages and behavior changes after a few hundred kilometers. It becomes very difficult to predict the human behavior as there are many factors like genetic, socio-economic, etc. Since humans are very comfortable with each other and try to live a social life. Being social is the common characteristics and it can be useful to predict the human behavior with respect to certain conditions. The impact of the internet on the social life of humans can be seen well. Social media forcing the people to use it and has become part of everyday life.

From the past 10 years, the tremendous rise has been seen in exploring social networking

[7] https://www.google.org/flutrends/about/
[8] https://www.google.co.in/trends/

sites for extracting information related to human psychology. Some surprising findings [12] were obtained such as popular ideas have some opponent of a certain percent and within a large group, only a few have leadership qualities. The dataset was collected from YouTube in real-time of anonymous random undergraduate students. The visualization reflects that the intrinsic complexity and obscure characteristics of web data, sometimes, make difficult to establish relationships among certain attributes.

3.1. Factors and theories of human behavior

There are many factors which influence the human behavior such as genetic, socio-economic, physical environment and psychological factors. The socio-economic and psychological factors play a vital role in social behavior. The factors like education, family, culture, self-concept, fear, anxiety, etc. directly associated with the social life. There are certain theories related to human behavior named as Bandura, Bibb Latane.

The Bandura theory [9][10] based on the concept of learning from others, which involves attention, retention, reproduction and motivation. Bibb Latane theory has three basic rules, the first rule considers how individuals can be "sources or targets" of social influences, the second is the social impact is the result of social forces including the strength of sources of impact, the immediacy of the event and the number of sources exerting the impact. Last is the more targets of the impact that exists, the less impact each individual target has. The impact of social influences on individuals has many forms and are visible in the comments and opinions given by the individuals to the others.

3.2. Opinion mining

Opinions are common to all human activities and are the key factors of our behaviors. Our beliefs and perceptions of the real world, and the choices individuals make, to a larger extent, depends on how others see and evaluate the world [5]. Opinions related concepts such as sentiments, evaluations, attitudes, and emotions come under the study of sentiment analysis and opinion mining. The rapid growth of social media on the web makes sentiment analysis as the most active research area in natural language processing. It is also the major part of data mining, Web mining, and text mining, and is widely spread from computer sciences to social sciences. Sentiment analysis has applications in almost every business and social domain due to its importance to business and society. Sentiment analysis can be broadly classified into three levels [15] based on the existing research problems: document, sentence, and entity-aspect level.

4. Subjective well-being

Opinions with emotions play such an important role in human decision making. Variations in human mood states have become a matter of considerable interest. The increasing importance of social media has made the researchers think about that how the mixing of psychological states affects in situations in the absence of physical contact. A system for sensing social systems has been introduced 9 years back, with data collected from 100 Bluetooth enabled mobile phones.

By using user modeling techniques to recognize social patterns in daily user activity, various features were given such as infer relationships; identify socially significant locations [7]. In the

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[9] http://web.stanford.edu/dept/psychology/bandura/pajares/Bandura2004 Me- dia.pdf
[10] http://psycnet.apa.org/doi/10.1037/0003-066X.36.4.343

present world of social media, another attempt had been done [2] to measure the happiness level of Twitter users. The results indicate that the online social media may be equally important subject to social mechanisms that cause assortative mixing in real social networks. The increasing prevalence of online social media may be an important factor in how positive and negative sentiments are sustained and spread through human society.

The sentiment analysis projects the perception of individuals and is an indirect measure of the personality. The personality of the individual, which determines the well-being of that individual. Well-being based on the personality of individuals is known as SWB. An attempt has been made to better understand the individual's personality by using Five-Factor model, which is a research model based on using natural language adjectives and personality based questioners. The model is a hierarchical organization of personality traits in terms of five dimensions: Extraversion, Agreeableness, Conscientiousness, Neuroticism and Openness to Experience [17]. SWB is a measurement of individuals evaluations of one's own life, which are largely based on the emotional well-being and positive functioning. Emotional well-being refers to a long-term assessment towards life and positive functioning encompasses of psychological, social wellbeing, and psychological well-being. Researchers defined multidimensional parameters by developing positive and negative affect scale (PANAS) [22] and psychological well-being scale (PWBS) [19]. PWBS based on positive functioning defines various parameters such as self-acceptance, the purpose of life, environmental mastery, positive relation with others, personal growth and autonomy items.

A state-of-the-art prediction model [8] was established to automatically sense individual SWB from the active users of SinaWeibo social network. The method was based on emotional well-being and positive functioning. The large data set from microblogs was used to sense individual SWB by training machine learning models. The model had very high prediction accuracy and can be applied to identify a large amount of social media users SWB in real time with low cost. The outcomes of the research invoke more researchers to study the happiness of individuals through the SWB.

Individual happiness is a fundamental metric of social well-being. An attempt had been made to measure happiness from the social media. Expressions made on the online social networking service Twitter were examined, which revealed the temporal variations in happiness and information levels over time. The text-based Hedonometer [6] measures happiness which is highly robust, tunable, remote-sensing and non-invasive. Hedonometer has been made available publicly on the internet [11] and is very useful to the researchers for future references. The varies results showing the happiness level variations are indicators to measure the SWB. In the above research, it is largely based on the happiness of individuals from the personal perspective. If the happiness needs to be measured based on the geographical location of individuals, effortless research, and novel architectures have been required.

Prediction of well-being was attempted by learning linear regression models on word counts in lexicons of emotionally-charged words with a large Twitter dataset. The choropleth maps produced, either at a state or at a country level, that show how well-being varies across the U.S continental [16]. SWB of individuals highly depends on the type of language the individuals use on social media. So, it is the words and phrases of the language used on social media, which characterize the SWB.

Recently, researchers used differential language analysis with particular open- vocabulary analysis to find language features that distinguish demographic and psychological attributes. The dataset contains over 15.4 million Facebook messages, further extracted into 700 million

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www.hedonometer.org

instances of words, phrases, and automatically generated topics and correlated with gender, age, and personality. The analysis shed new light on psychological processes that suggest the relation of personality to the language used on social media [20]. The above study analyzes every user on social media, therefore, lacks in the value of data and contain a high amount of noise in the dataset. To reduce these factors, the dataset should be precise, and to raise the value of data, active users of social media should be targeted.

The prediction [14] of the personality of active users on micro-blogging platform SinaWeibo was carried out by Big five personality traits. Total 845 microblogging behavioral features were extracted and classification models utilizing Support Vector Machine (SVM) was trained. Participants scores were predicted on each dimension of Big-Five Factor Inventory with classification accuracy ranging from 84% to 92%. The results indicated that it was possible to predict the active user's personality with high accuracy and the micro-blogging services of non-US based social media sites. The above examples of research indicate the positive effect of the usage of social media on SWB of individuals. However, as discussed earlier the social media also have negative consequences on SWB. High usage of social media may affect the personal life and behavior of individuals toward to others.

The social and psychological well-being (social success, normalcy, and selfcontrol) are key factors in human behavior. A recent study examines the impact of media multitasking behavior on university student's well-being [23]. The study characterized media multitasking behavior by motivations, characteristics, and contexts. The findings suggested that synchronous social interactions are significant and positively associated with social success, normalcy, and self-control. However, high usage of social media in synchronous social interactions reduced the individual's social success. Social networking sites offer a lot of features, which may be the strong reason behind the usage addiction of social media.

The usage addiction of social media can lower the performance of an individual! To study this classroom task environment was created to measure the usage of social media and task performance [3]. It was found that higher amounts of social media usage led to a lower performance on the task, as well as higher-level of techno stress and lower happiness. The results suggested that the usage of personal social media during professional times can lead to negative consequences. The negative effects of high social media usage have a huge impact on adults which are highly active users of social media.

Social media theory suggests that adults evaluate good and bad consequences of social relationships they experience, so a study was carried out to report good and bad perceptions of social media, with perceptions varying according to demographic and psychological characteristics [11]. The demographic variables revealed that younger individuals had good perceptions and bad perceptions by those who had health problems. Analysis of psychological variables suggests that good perceptions were reported by angry individuals with strong friend supports and bad perceptions by angry individuals with low self-esteem.

Also, a study [4] investigated 1) patterns of media use for social sharing and 2) effects of social sharing on sharers well-being. The results revealed the positive events were more shared on online social media and negative events via face-to- face. Regardless of the medium, users shared positive event experienced positive affect and who shared negative event had increased the negative effect.

5. Conclusion and future work

In this paper, we reviewed the research papers of social media focused on individual's subjective well-being. In the first section, we discussed that the big data is the backbone of social media. In the next section, we have discussed the well-known theories based on human well-being. These theories helped the researchers to set the parameters to predict the human well-being. The trend of social media is very popular and people share their feelings on social media, provides large data related to subjective well-being. The researchers used that data to study the well-being of individuals. The higher accuracy of results and predicted outcomes was very impressive, thus gained a lot of attraction. More researchers are now attempting to get into new insights of social media analytics focusing on subjective well-being. As the data is changing rapidly, so many scientists faced different challenges such as high noise, real-time analysis of data, etc. The real-time prediction of subjective well-being from social media may be the hot topic of future research. The real-time predicted happiness of people will be shared with friends and family. Hence, it may provide a better environment as people will adjust their mood levels according to the other individual's behavior.

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