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EXPLORATORY ANALYSIS OF SLEEP PATTERNS AND FACTORS USING TWITTER DATA

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ABSTRACT

Online networking examinations on various social media platforms can reveal impressive insights into human conduct, increasing factual quality from the size of such connections. Not many studies have been conducted on how demographics and geographic data are related to social media activities to predict day-to-day human activities or their precise sleeping cycles. In this paper, we break down Twitter information to extract knowledge regarding factors influencing how much sleep different populations get. Reduction in sleep duration can be influenced by various factors including time zones, weather, age, seasonal impacts, and even locations. We have utilized Twitter data timestamps, location geographical tagging, and personal bios of Twitter users to analyze the sleep pattern influenced by such external factors. To establish a better relationship between Twitter activities and the demographics and geographic factors, Twitter activities from all the US states, and European and Asian countries over the period of a few months in a year were analyzed. Based on our observations and analysis we may assert, that connecting social media activity to geographic and demographic variables can aid in our understanding of daily anthropological activity.

Keywords: Exploratory Analysis, Twitter, Sleep Analysis

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I. INTRODUCTION

The antagonistic impacts of the lack of sleep on people are broadly acknowledged. However, there is not sufficient analysis available on how various factors are influencing sleeping patterns and their impact on people. A sleeping disorder, which is portrayed by the difficulty to fall asleep or staying asleep throughout the night, is one of the well-known issues in the United States and throughout the world. About one-third of the grown-up populace in the US encounters sleep deprivation eventually in their lives [1], and it is a persistent problem among approximately 10% of U.S. adults [2]. Previous works include analyzing the impact of late-night social media activities on NBA players' game performances [3]. Their work proved that late-night social media activities impact an athlete's next-day game performance. Analysis has been done on the interactions between signal degradation and sleep deprivation effects [4]. It implies that rather than altering arousal in general, the consequences of sleep loss are uniquely tied to the nature of ongoing cognitive functions. Apart from external and social factors, medical conditioning can impact the level of sleep among people. Numerous medical and neurological conditions, psychiatric disorders, pain, drug therapy, and the hospital setting can all interfere with sleep and make it harder to recover from illness [5]. In this study, we will analyze tweets over a significant period of time and utilize the various metadata and actual tweet data to get insights into how much sleep different populations get.

Furthermore, studies suggest that in people who are not using alarm clocks or electric lights, their sleep-wake cycles shift to align to sunrise and sunset [26, 27]. In this era where entertainment and social interaction are ubiquitous around the clock, many people live out of synchrony with the day-night cycle [28, 29]. In order to approximate how such social pressures disrupt the natural sleep cycles of human beings, Roenneberg et. al introduced a term named "social jet lag", which can be defined as "the difference between the midpoints of sleep and free days" [22]. Studies have shown that the mismatch between sleep time and work and free days can have negative consequences for human health [30, 31]. In this study, we focus also on analyzing how social jet lag are being affected by various factors such as the seasons of the year, age, socio-cultural factors such as employment status, and so on.

II. DATASET

Twitter is a cell phone and Web application that enables clients to freely post short messages called tweets. It is an online networking stage utilized by 24% of entire U.S. adults, with as much as 45% by those within the age range of 18-24 alone [6]. For the purpose of this project, we obtained the raw unprocessed Twitter dataset from *TrackMyHashtag.com*; the dataset comprises weekly tweets of 24 hours from May and December 2017 and May and December 2018.

The Twitter data consists of JSON objects, namely Tweets and Users which encapsulate the core attributes that describe each Tweet and the associated user object. Each Tweet includes an author, a message, a special ID, the time it was tweeted in the user's specified display time zone, and occasionally, geospatial metadata that they have shared [11]. Each User has a Twitter name, an ID, a number of followers, a URL linked to the profile photo, and most often an account bio or self-description [11]. These attributes, appearing as columns, are the features of the dataset we are analyzing and the quality of these features has a major impact on the quality of the insights that our study can gain from these data [12]. *TrackMyHashtag.com* provides us with a separate file containing the *Tweet IDs* from above along with users' original profile picture *URLs*.

1. For more granularity in time series analysis we extracted the below attributes from the tweet created date field tweet object: *time, minute, hour, date, day, weekday*
2. Also, since one of our target areas included analyzing patterns across countries and continents, hence we populated country and continent attributes from the place name field in the tweet object. To do so, we looked up the text data in the place field and matched it with the list of cities/countries to find the country name.
3. Another aspect of our analysis included visualizing trends across time zones and hence we populated the time zone attribute using the country and place field created above. We extracted the name of the city from the place field if present; otherwise, we used the country name and looked up the time zones for the respective countries/cities.
4. A major issue with Twitter data is the presence of bot-generated tweets. To detect such tweets in the *TrackMyHashtag* dataset data, We calculated the likelihood that a Twitter user is a bot using machine learning using the R package *botornot*. The baseline model is based on gradient boosting trained on both user and tweet levels, where the user level includes their bio, followers, location, etc., and the tweet level includes mentions, hashtags, etc. The model has shown an accuracy of 93.53% when it tried to classify bots while it showed 95.32% accuracy for non-bots classification.

AA. FACTORS AND DATA TO BE ANALYZED

First, we analyze the timestamp associated with each tweet. We utilize the timestamp and time zone to infer the local time when each tweet was sent by the user and thereby be able to get a sleep pattern for that particular population. This information has been previously utilized to estimate the mood of a person according to the time of the day [7] and to analyze the sleep schedule of President Trump [8]. Several external factors can be taken into consideration for sleep pattern analysis. For the purpose of this study, we focus on

1. Seasonal effects: The hour of dawn fluctuates with scope and season. Sensible speculation is that dawn influences the time individuals stir toward the beginning of the day. We aim to demonstrate wake-up times by place for each of the seven days of the year and gain insights on whether an individual's sleep cycles are in sync with their wake-up times or find out whether individuals are getting more sleep in winter than in summer.
2. Occupation: Twitter has a section called *bio*, a string that contains a brief self-reported description of a user that can give us insights into how Twitter users view themselves. More often than not it reveals the occupation they are associated with or how they usually spend most of their days.
3. Demographic impacts: Twitter does not require or record its users' age or date-of-birth attributes. Levi and Hassner demonstrate that deep-convolutional neural networks (CNN) can provide increased performance in face recognition tasks [20] and provides a benchmark of face photos that facilitates the study of age and gender recognition. To predict the age of Twitter users for our analysis, we scrape Twitter users' profile photos using their profile photo URLs provided by *trackmyhashtag.com* and using labeled data from Levi's dataset, we train a model using deep-CNN to extract image features from Twitter profile photos and then predict the age of Twitter users in our dataset [9].
4. A time-series analysis: With data being available for almost half a decade it is possible to get a time-series visualization of how people's sleep duration has increased or decreased over time. We normalize our results given the fact that the popularity of Twitter among users has not been the same in the past compared to now. Below [Fig 1] is a small distribution of the number of tweets per hour for total available users using

TrackmyHashtag data. We used 24 hours of data over one week from May and December 2017 and May and December 2018.

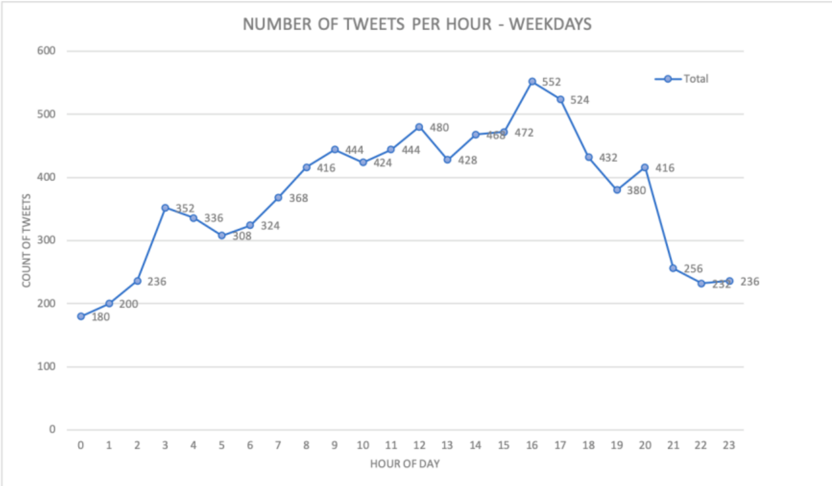

Figure 1. Tweets per hour by the total population of Twitter users

We designed a metric to approximate the average sleeping hours of Twitter users based on their Twitter activities.

First, we calculated the distribution of tweets for each user throughout the 24 hours of a day. Next, we infer when a user wakes up and goes to bed at night. For our study, we assume that the normal sleep cycle of an adult is between the hours of 10:30 pm and 6:30 am.

Sleeping hours for an individual are hours within our assumed sleeping time interval when the Twitter activity is below a threshold level. This value is denoted as the number of hours an individual sleeps every night and is used by us to calculate the average sleep hours.

In order to select a reasonable 'threshold', we tried multiple metrics like mean, median, half of median, and half of the mean and tested different values of threshold on our dataset. Initially, we tested with mean-by-two, median-by-two, mean-times-half, median-by-two, and median-by-three thresholds. We tested each of the thresholds against 20 users whose sleeping cycle and Tweet behavior we already know (e.g. family members, roommates, and ourselves). Our analysis reveals that median-by-third is a more accurate predictor of the sleeping cycle of an individual. As a result, we use median-by-three as a threshold for this study.

III. EXPLORATORY DATA ANALYSIS

We utilized tweets from *trackmyhashtag.com* to perform our initial analysis to analyze a time series pattern. Since some of the attributes (i.e. features) in the Tweets were redundant for our study, we selected only those that are useful for our analysis (i.e. timestamp, text, place, profile image URL, user bio).

Over five percent of the Tweets collected had missing timestamp values (i.e. 'NaT' for the 'created_at' attribute). As timestamp is an independent feature that other features depend on, we dropped all such rows with missing timestamp values.

Based on the gender of a user, the informativeness of the tweet can vary. By utilizing this fact, we predicted the gender of a Twitter user from the tweets of the user [10]. [Fig 2] and [Fig 3] represent the tweeting patterns of Male and Female users over the course of the day. From the dataset provided by *trackmyhashtag* we can observe that women seem to have a more erratic sleeping pattern as compared to men.

AA. AVERAGE SLEEP TIME BY GENDER

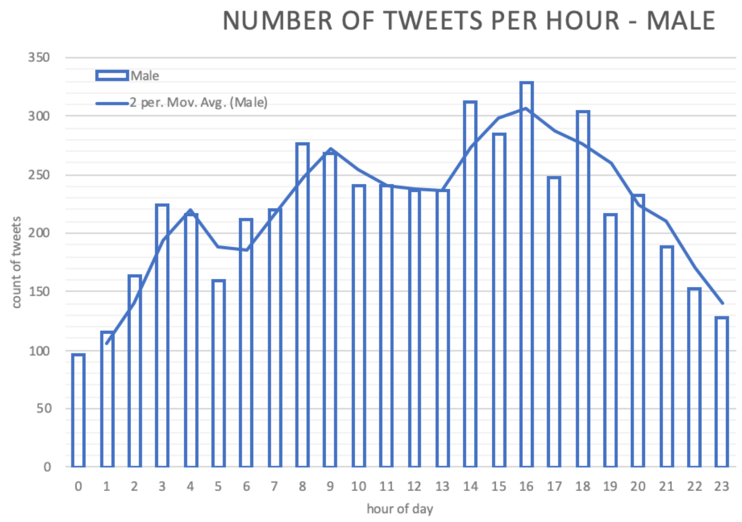

Figure 2. Tweets per hour for Male Twitter users

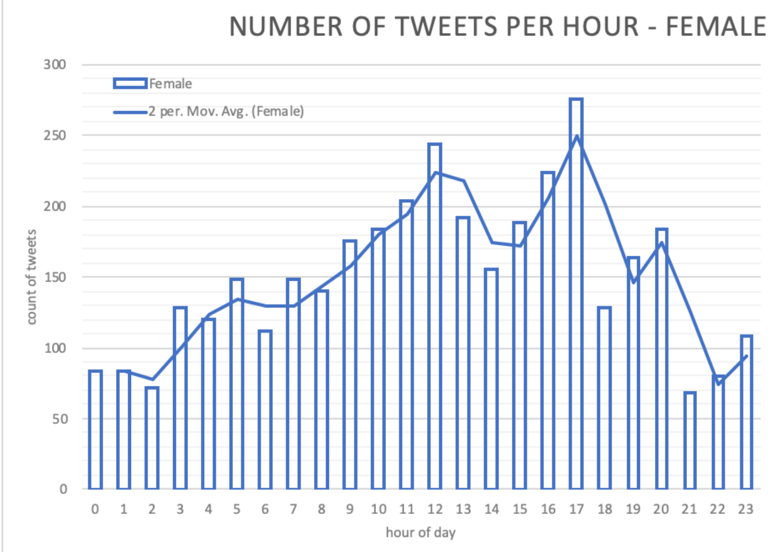

Figure 3. Tweets per hour for Female Twitter users

Applications in social science, economics, and business could employ demographic lexica extensively [15]. Before we can classify Twitter users between male and female, we need a predictive lexica (i.e. words and weights) for gender. Sap et al. by utilizing regression and classification models from word usage in Facebook, blog, and Twitter data with related demographic labels, have constructed predictive lexica for general use [15]. Implementing the methodologies outlined in "Developing Age and Gender Predictive Lexica over Social Media" and using the pre-built lexica that achieved state-of-the-art accuracy (i.e. 91.9%) in language-based age prediction over Twitter users, first, we trained a model and then used it to predict the users' gender from the words in their tweet texts.

To implement the model we used a gender_intercept = -0.06724152. This prediction function returns a float where the positive value represents the female and vice versa. For future work, we plan to identify the gender of a Twitter user by his/her profile picture using Deep learning. Currently, we did not use this method because a user might not put up his/her own picture and it might be some random images that will not help us yield a gender.

On the other hand, generally, users have multiple tweets and the probability of having text content in at least one of them is high. Thus, there's a better probability for us to detect the gender of a user using textual data.

From [Fig 4] and [Fig 5] we can observe that for female users there is a spike in the number of tweets during weekends which affects their sleeping pattern, whereas for men the spike is particularly during the early weekdays and they comparatively have a quieter weekend.

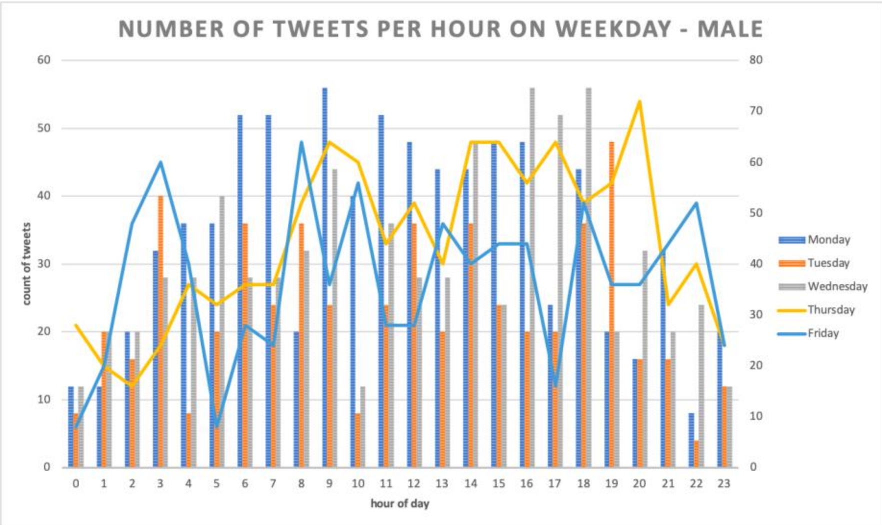

Figure 4. Tweets per hour per day for Male Twitter users

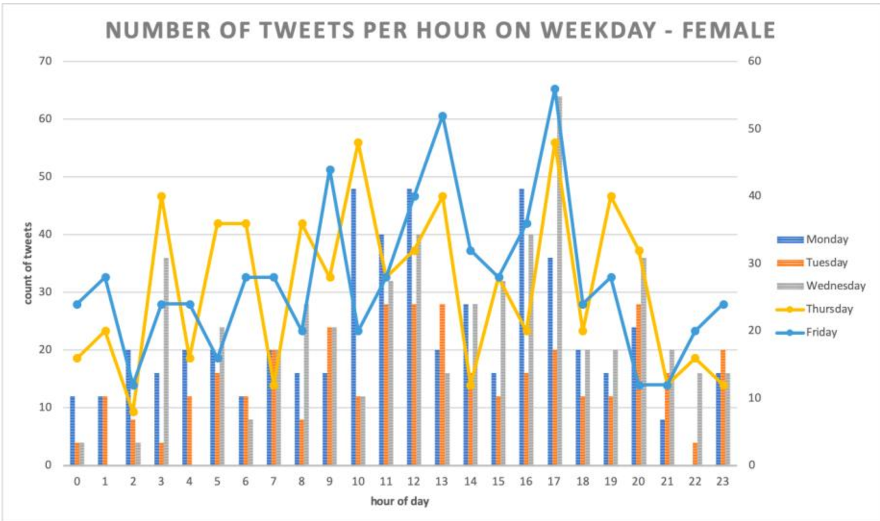

Figure 5. Tweets per hour per day for Female Twitter users

BB. AVERAGE SLEEP TIME BY AGE

Age is one of the determinants that bring about changes in a person's personality, typically becoming less open to experiences but more agreeable and conscientious [16]. Moreover, word usage in social media varies by age [17, 18] and gender [19]. Since the emergence of social platforms and social media in recent years, automatic age and gender classification have been pertinent to an increasing number of applications.

[Fig 6] and [Fig 7] tell us that the age group of 30-40 shows maximum activity on Twitter and hence has the least number of average sleeping hours, whereas the older age groups show significantly less activity on Twitter and have a better average sleeping hour as expected.

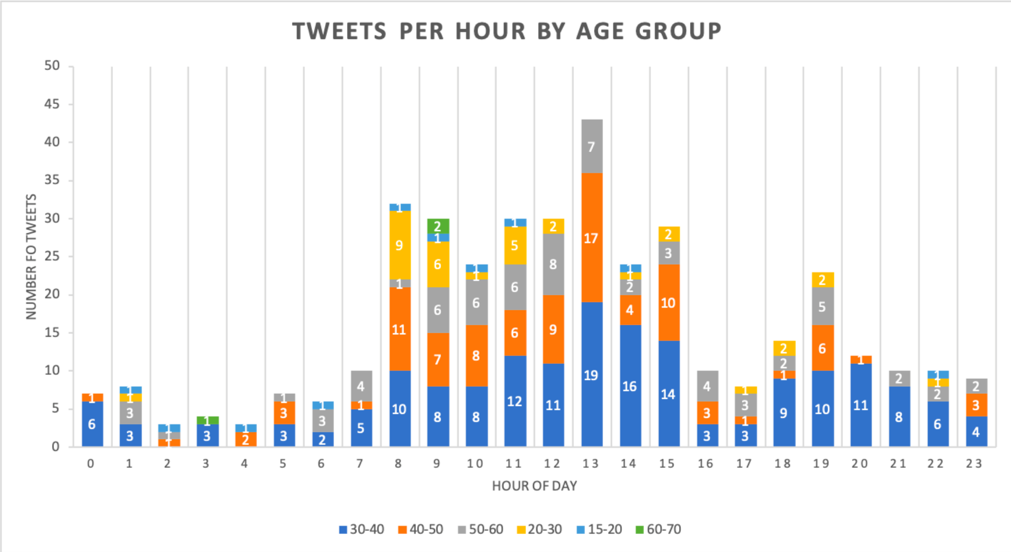

Figure 6. Tweets per hour for different age groups

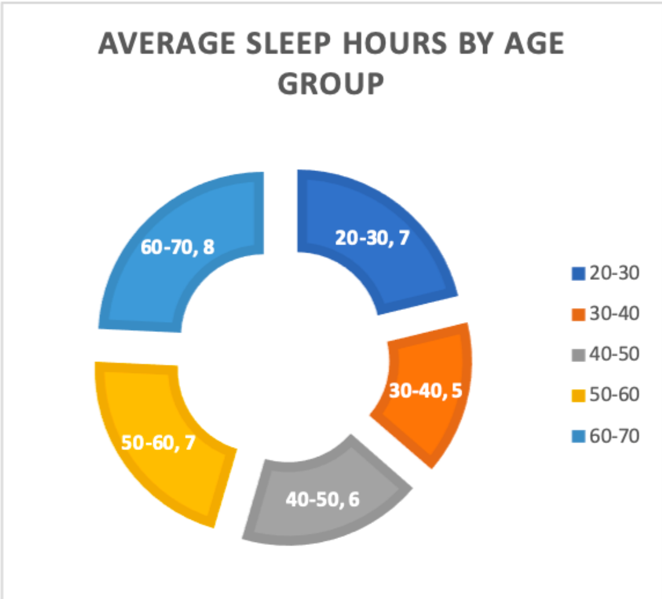

Figure 7. Average sleep hours by age group of Twitter users

Twitter does not require or record its users' age or date-of-birth attributes and most Twitter users do not mention their age in their bios. In the paper "Age and Gender Classification Using Convolutional Neural Networks", Levi and Hassner demonstrate that deep-convolutional neural networks (CNN) can provide increased performance in face recognition tasks [20]. As face photos from social media prove to be an efficient indicator of a user's age, we realized that Twitter users' profile photos can be a useful tool to predict their age.

From the Twitter dataset, the *user* object contains the *profile_image_url* that provides the profile photo of each user [29]. In that way, we obtain the profile photo of each user in our dataset. Levi and Hassner provide a dataset and benchmark of face photos that facilitates the study of age and gender recognition [21]. The data are based on real-world imaging tasks and conditions, and they try to show the differences in look, noise, pose, lighting, and other things that can be seen in pictures that weren't carefully set up or posed [21]. We use this labeled data of face photos to train a model using a CNN to extract the image features and predict the age of users against their profile photos that we retrieved.

To train our network we used the following hyperparameters and configuration: number of epochs: 30, initial learning rate: 0.1, optimizer name; 'SGD', depth of network: 16, width of network: 8 and a validation split ratio of: 0.1.

Without data augmentation we were getting a loss of approximately ~4, but it reduced to around ~3.6 with mix up and random erasing data augmentation.

CC. AVERAGE SLEEP TIME BY OCCUPATION

Since there are no ‘occupation’ attributes that Twitter data contains, there was no direct way to figure out the ‘occupation’ of Twitter users. Twitter has a section called *bio*, a string that contains a brief self-reported description of a user that can give us insights into how Twitter users view themselves. More often than not it reveals the occupation they are associated with or how they usually spend most of their day. Previously, Preoţiuc-Pietro et al. predicted occupational classes for Twitter users with no bio [13]. In another study, the Tweet ‘text’ was analyzed for mapping users to one of the nine Standard Occupation Classifications (SOC) [14].

We create our own training set by tracking accounts with bios for self-disclosed occupational titles each categorized from one of the nine unit groups. Accounts that contained no occupational description and could not be categorized were discarded. In addition, company accounts and bots were discarded to enhance the quality of our training data. Using the nine categories as a reference list of occupations, we performed a search and extracted the list of users who matched the longest matching job title descriptions, including cross-overlapping matches, together with the start and end positions in the given bios of the users.

[Fig 8] and [Fig 9] give us a picture of how erratic the sleeping style of healthcare professionals can be, given the unpredictability of their jobs. On the other hand, sportspersons and government officials, seem to sleep around 3 hours more than healthcare professionals. This aligns with our assumption because healthcare professionals usually have to spend long hours at work whereas for sportspersons it is almost a necessity to sleep for such a duration.

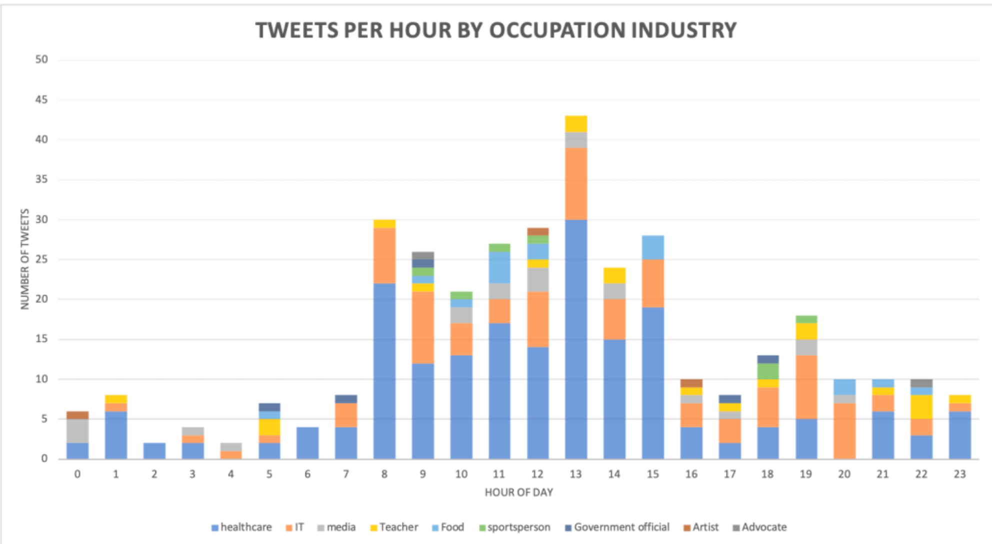

Figure 8. Average tweets per hour by occupation in different industries

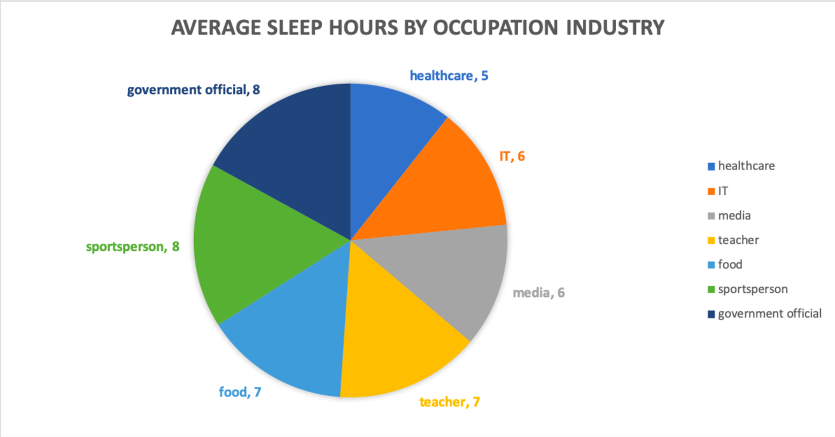

Figure 9. Average sleep hours by occupation per industry category

DD. AVERAGE SLEEP TIME BY COUNTRY

As per research by the National Sleep Foundation, every adult human being requires on average 7 to 9 hours of daily sleep [23]. Do people in America sleep enough? Surveys have shown that Americans get almost eight and a half hours of sleep each night whereas people in China sleep one hour more than the Americans [24].

Analyzing the historical Twitter data from *trackmyhashtag.com*, we plotted [Fig. 10] for the top four countries whose data were available and we discovered from [Fig. 11] that Americans sleep on average 7 hours which almost aligns with Gallop Poll's findings of 6.8 hours every night [32].

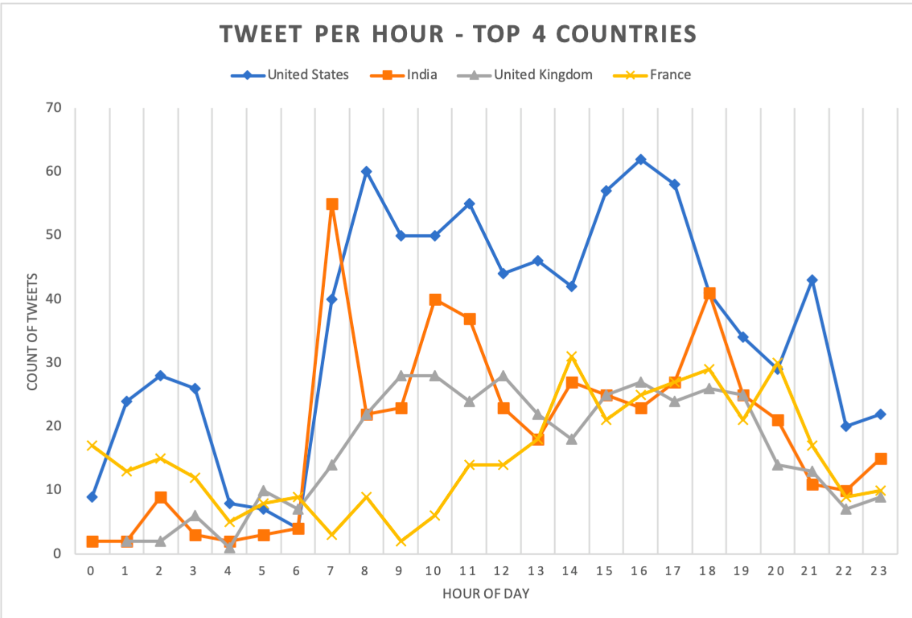

Figure 10. Average number of tweets per hour by country

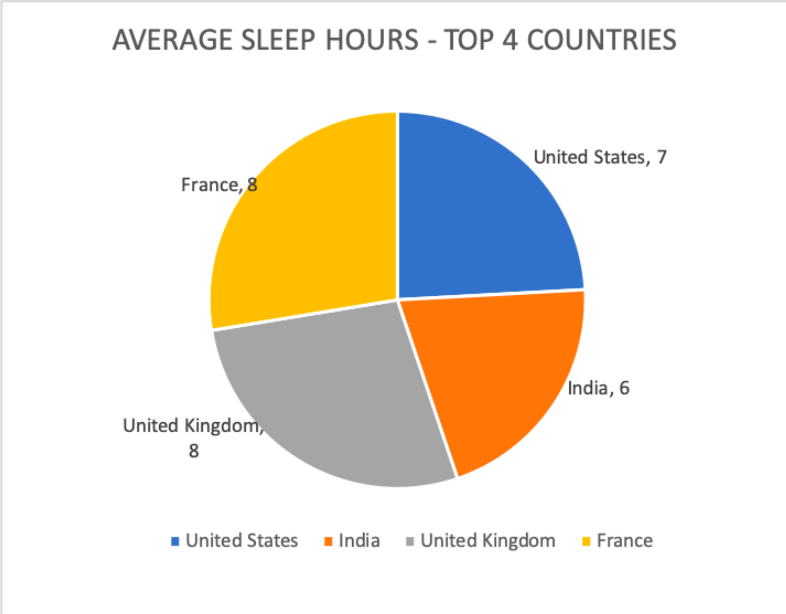

Figure 11. Average sleeping hours in the top four countries

Furthermore, based on *trackmyhashtag.com* dataset we observe from [Fig. 10] that Americans tweet the most, particularly with peaks between 8 and 9 am (right before their office starts) [Fig 10]. The findings also reveal that the other time of the day when Americans tweet the most is between 4 pm and 5 pm (right before office hours end). These findings align with our assumptions that people tend to spend more time on social media during their personal hours or at the end of their workday when they are tired or ready to leave the workplace.

EE. AVERAGE SLEEP TIME BY TOP 3 CONTINENTS AND TIME ZONES

As one of the target areas of our study involves analyzing patterns across countries and continents, we populated country and continent attributes from the *place* name field in the tweet object. We obtained the list of cities and countries from the World Cities Database [25]. By looking up the text data in the *place* field and matching it with a list of cities and countries, we got the country name. [Fig 12] illustrates our findings; here we display the average tweets per hour for three out of the seven continents.

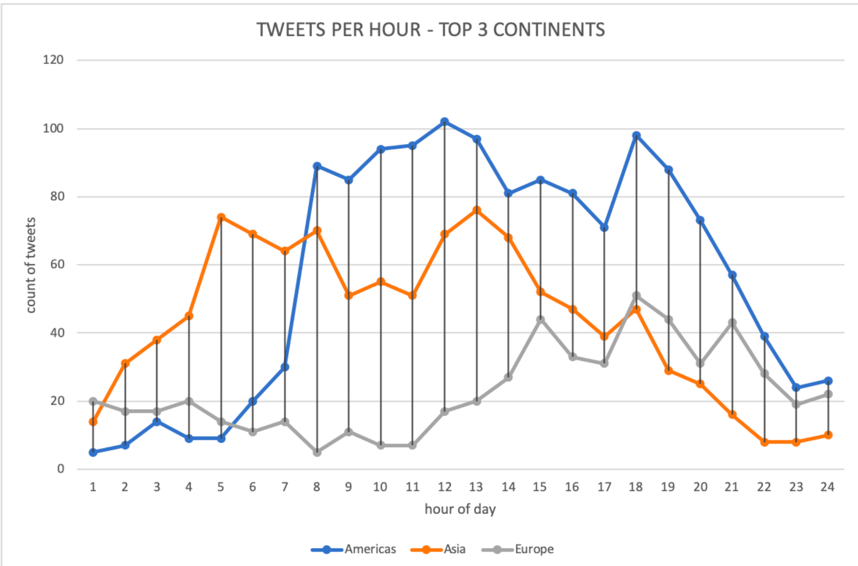

Figure 12. Average tweets per hour by continent

We also created a dashboard as in Figure 13 to show the number of tweets per hour by day and continent.

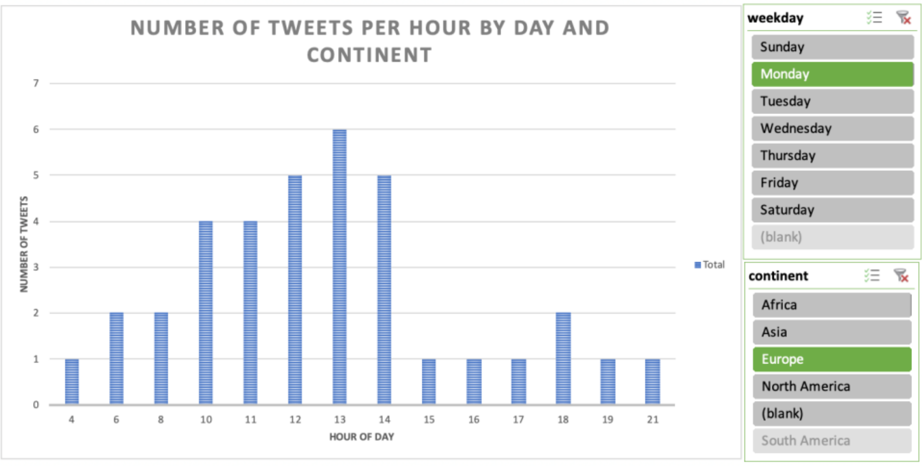

Figure 13. A dashboard displaying average tweets per hour by days of the week by continent

Another aspect of our analysis includes visualizing trends across time zones and hence we populated the time zone attribute using the *country* and *place* field created above. We extracted the name of the city from *place* field if present; otherwise, we used the country name and looked up the time zones for the respective countries and cities from Word Cities Database. Our findings are shown in [Fig 14] where we see that the average sleeping time among users residing in Europe and America is 7 hours every night which aligns with our findings from the previous section. [Fig. 15] illustrates the top four timezones with respect to the number of tweets per hour and [Fig. 16] displays the average number of sleeping hours across four time zones. Indeed, this again aligns with our assumption that people living in the US or in populated cities in India in Asia may be more exposed to social media platforms such as Twitter which may be one of the causes for their fewer sleeping hours.

Figure 14. Average sleeping hours in top three continents

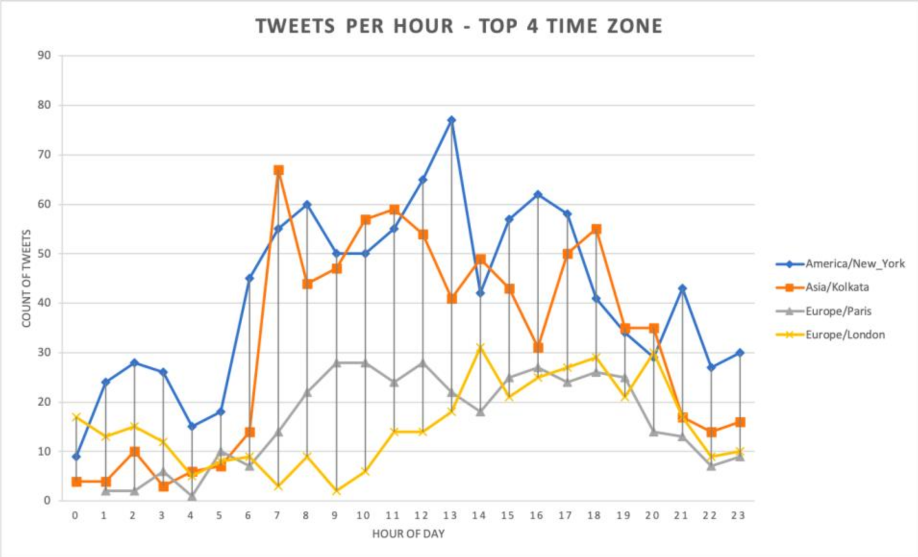

Figure 15. Tweets per hour in the top four timezones

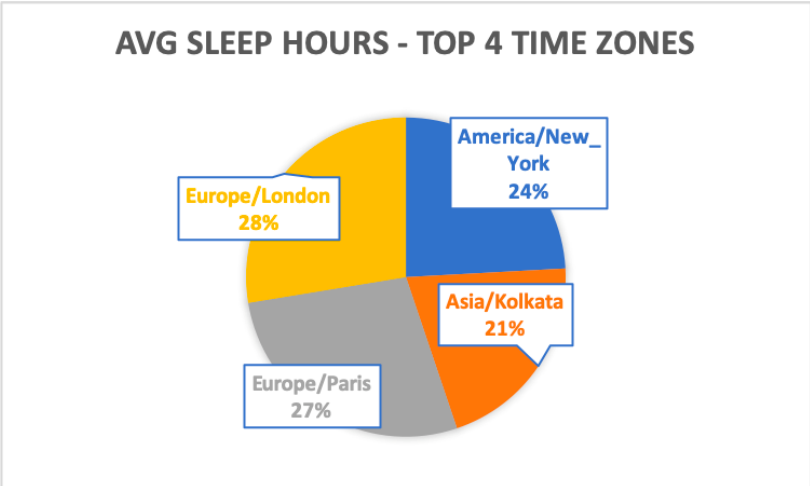

Figure 15. Average sleeping hours in the top four timezones

IV. CONCLUSION

We have gained valuable insights from our study. Temporal and geographical patterns of Twitter use reveal a widespread impact on people's sleep hours. We have utilized Twitter data timestamps, location geographical-tagging, and personal bios of Twitter users to analyze the sleep pattern and to establish a better relationship between Twitter activity and the demographics and geographic factors. Our analysis reveals that Asian countries experience a significantly greater impact on their sleeping hours as compared to Western countries. We also observe that younger and middle age group people are positively correlated with more Twitter usage and lower sleep hours as compared to the older age group. We can thus claim based on our analysis and observations that correlating social media activity with demographics and geographical factors can help us analyze the day-to-day human activity. For future work, the prediction of other human activities apart from sleep cycles can be explored from such social media data. Also, problems like obesity or other health issues which do have a positive correlation with the amount of social media activity can be addressed and counteractive measures can be developed.

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