Understanding The MeToo Movement Through The Lens Of The Twitter

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Abstract. In recent years, social media has provided platforms for raising the voice against sexual harassment (SH). The *MeToo* movement is one such online movement that aims to show the magnitude of this stigmatized issue in society. In particular, on *Twitter*, which is the focus of this study, has attracted a large number of tweets from all over the world regarding the *MeToo* movement. The studies of the *MeToo* movement focus on the SH and sexual assault (SA) incidents but fails to analyze its other hidden facets. In this work, we perform micro-analysis of the *MeToo* movement using tweets and present a descriptive analysis coupled with macro level tweets analysis in order to reveal and understand the diverse subtopics of the *MeToo* movement. In addition, we also identify and characterize varied user-groups derived through social network analysis. We find that users discussing a similar facet forms a strong community. Some of the facets out of many being discovered are as follows (1) SH incidents reporting is high for people of color[1]; (2) discussion over color often leads to the use of hate and offensive vocabulary; and (3) along with workplaces, domestic SH cases are higher.

Keywords: MeToo Movement · Twitter · LDA · NLP · WordCloud · Social Network Analysis.

1 Introduction

Social media platforms, particularly Twitter, is often used for online social movements [30]. Several studies [33, 19, 27, 1, 14] have explored tweets data to understand various social movement such as anti-discrimination, awareness, political, and women's rights, to name a few.

In this study, we focus on a particular online movement termed as *MeToo*. The phrase "*MeToo*" was initially used on myspace, an online social media platform, in 2006 by sexual harassment (SH) survivor and activist Tarana Burke [24]. However, the phrase attracted a lot more attention when Milano tweeted it around noon on October 15, 2017. It was used more than 200,000 times by the end of the day [31], and was tweeted more than 500,000 times by October 16, 2017 [13].

[1] color means other than white

In this work, we analyze the 3.5 million *#MeToo* tweets of 1.03 million users, collected using Twitter API over a period of ∼5 months to cover the following research directions:

1. **Revealing the hidden facets:** In each of the online social movements, some facets are more evident than others. We termed these not so evident facets as hidden facets, which are often not easy to detect as they are the topics of discussion of a smaller group, which gets buried under the heap of more popular topics. Our findings show that the *MeToo* movement covers many hard-to-see facets apart from Sexual Harassment (SH) and Sexual Assault (SA) such as (1) SH incidents reporting is high for people of color[1]; (2) discussion over color often leads to the use of **hate and offensive vocabulary**; and (3) majority of SH incidents belong to workplaces or are domestic, compared to public places (Section 4).
2. **Topic aligned communities:** To understand user interactions with respect to various subtopics in the online *MeToo* movement, we employ social network analysis techniques. We observe that users tend to create communities based on topics of their interest. We also identified leaders of these communities. By leaders, we mean users who are retweeted a relatively higher number of times. We also observe that the content from activists, journalists, and media profiles gets more acknowledged (Section 5).

Various researchers have worked on the topic of *MeToo* movement either by using qualitative methodologies such as surveys and questionnaires or using a small amount of data and focusing on one particular facet such as feminism [15], men's psychology [32, 26], SA places [18] and the role of social platforms [22]. To the best of our knowledge this is the first work which has analysed such a large datasets and revealed hidden facets along with the intuitively evident facets of SH and SA in the *Metoo* movement.

The rest of the paper is organized as follows. Next, we discuss related works. We then describe the dataset in Section 3. In Section 4, we reveal the hidden facets of the *MeToo* movement. Section 5 studies the topic aligned communities and leaders. We conclude with a discussion of future directions in Section 6.

2 Related Work

In this section, we discuss relevant literature with respect to the *MeToo* movement, which involves two different lines of work. First involving qualitative analysis and second using quantitative analysis. Qualitative analysis works are based on surveys, interviews with survivors or public opinion, whereas data from online social platforms or records of SH and SA incidents are used for quantitative analysis.

Qualitative analysis. In [15], the authors explain that the *MeToo* movement is making a change in the era of feminism by helping women to share their anger and stories, which is challenging to do otherwise. They also state that under *#MeToo*, a few men have also shared their stories. [32] and [26] study the psychology of men and masculinity in the *MeToo* movement. They highlights that in response to the *MeToo* movement, some men in positions of power are afraid to participate in mentoring relationships with women. In [17], authors exclaim that being afraid to mentor women is not simply about fearing false accusations of sexual misconduct rather it is about discrediting women who speak out against sexual assault and harassment.

In other work [16], authors discuss the SH in medicine. This highlights that the SH and SA incidents exist among educated and esteem professions as well. Despite this, the reporting of SH incidents is limited and the main reason behind hiding these incidents is that people tend to avoid or are afraid to talk about SA [29]. The issue of SA and SH are spread in defense forces as well. For example, there are several studies to support and protect victims and to hold culprit liable in the army [11].

In a different work [25], authors focus on highlighting the critical points to explain why the experiences of women of color are ignored in the *MeToo* movement. They argue that the presence of racial biases in the movement shows that the SH doctrine must need some reasonable improvements.

Quantitative analysis. In another line of work [22], authors present how individuals on different platforms (Twitter and Reddit) share their own experiences and respond to the experiences shared by the others. Their research shows that Reddit allows individuals to share their personal experiences in-depth while individuals on Twitter prefer to follow the *MeToo* movement with others. In [18], the authors try to identify the risk factors associated with SA places. Deep learning-based lexical approaches are used in their study to identify SA in terms of locations and offenders.

This work is different from the existing studies as the focus of previous works were mostly on analyzing a single facet of the *MeToo* movement considering some prior knowledge or assumptions. However, in this work, we extract the hidden facets apart from SH and SA under the *#MeToo*. These subtopics are extracted directly from the collected tweets' data without any prior assumptions.

3 Dataset Description

This section provides information about the usability of Twitter, an online social media platform for understanding social movements. The procedure of collecting and pre-processing the Twitter data is addressed in the following subsections.

3.1 Twitter and Social Movements

Twitter[2] is an online social media platform classified as a microblog with which users can share messages, links, images, or videos with other users. There are other microblogging platforms such as Tumblr[3], FourSquare[4], Google+[5], and

[2] http://twitter.com
[3] https://www.tumblr.com/
[4] https://foursquare.com/
[5] http://plus.google.com

LinkedIn[6] of which Twitter is the most popular microblog launched in 2006 and since then has attracted a large number of users. As of 2019, Twitter has more than 326 million monthly active users[7].

In recent years, *Twitter* has provided a platform in facilitating discussions regarding stigmatized issues in society through online activism [10]. An online activism is considered as an effective way to broadcast a specific information to large and targeted audiences on social media [8, 23]. One way to achieve this is by using hashtags, also known as "Hashtag activism" [21, 8, 6, 23]. This is the act of showing support for a cause through a like, share, comment, etc on any social platform. The hashtag activism on Twitter covers multi-dimensional real-world issues like **Human rights** (#BlackLivesMatter, #IStandWithAhmed, #YessAllWoman, etc), **Political** (#ArabSpring, #NotOneMore, #NODPL, #UmbrellaRevolution, etc), **Trends** (#icebucketchallenge, #ALS, #Hallyu), **Awareness** (#FakeNews, #AmINext, #HimToo, #MeToo, etc) and others.

3.2 Data Collection and preprocessing

This work utilizes the dataset which has been collected using Twitter's Streaming Application Programming Interface (API) and Python (*tweepy* package) for 5 months (Oct 2018 to Feb 2019) of tweets containing either "metoo" as hashtag or keyword. The size of the collected dataset is 6.5 GB, containing 5.1 million tweets.

Parameter	**Value**
Time period	30-09-2018 to 18-02-2019
Total number Of tweets	3,529,607
Number of original tweets	870,516
Number of unique users	1,034,831
Number of unique features	91
Tweets with username	1,335,885
Tweets with hyperlink	2,306,485
Tweets with one hashtag	1,935,752
Tweets with two or more hashtags	1,593,855

Table 1: Statistics Of The Dataset.

On initial investigation, we find that some tweets containing *MeToo* as part of the tweet, but not having the hashtag (*#MeToo*) is irrelevant. Therefore, we remove the tweets without the *#MeToo*. Furthermore, we observe that tweets that contains large number of hashtags are often promotional and not link to

[6] http://linkedin.com/

[7] https://eu.usatoday.com/story/tech/news/2017/10/26/twitter-overcounted-active-users-since-2014-shares-surge/801968001/

S.No.	Words	Topic (Proposed)
1	white, sex, black, brown, money, hollywood, racism, rapist, free, color	People of Color
2	sexual, harassment, assault, abuse, report, violence, public, law, issues, workplace	Places of harassment
3	fake, victims, rape, start, real, victim, person, false, true	Trust deficit among users
4	shit, hard, hell, fuck, accused, feel, stop, bad, wrong, call	Hate and Offensive vocabulary
5	woman, life, girls, sexually, day, happened, girl, raped, assaulted, remember	Female sexual harassment
6	court, vote, justice, political, left, ford, evidence, democrats, guilty, innocent	Role of justice system
7	allegations, media, hollywood, accused, news, align, industry, bollywood	News and media industry
8	speak, read, survivors, hope, talk, coming, forward, powerful, speaking, voice	Public speak-outs for survivors
9	power, world, male, change, respect, society, gender, rights, fight, culture	Role of world, society, gender and culture
10	time, love, female, video, watch, hard, era, consent, ladies, lady	Feminism on Twitter

Table 2: Topic Modelling using LDA with Gibbs sampling.

the actual *MeToo* movement. These are removed using the outlier treatment method. For outlier treatment, we follow the standard statistical method of 1.5*IQR, where we follow the IQR (Inter Quartile Range) of the number of hashtags. Based on the distribution of co-hashtags, we removed tweets containing more than 4 hashtags. Finally, after the cleaning process, our dataset contains 3.5 million tweets from 1.03 million unique users. Table 1 summarises various statistics about this dataset.

4 Hidden Facets Of The *MeToo* Movement

This section's focus is to reveal the hidden facets of the *MeToo* movement along with SH and SA on Twitter. We use the topic modelling technique to extract these subtopics. In particular, we use the Latent Dirichlet Allocation (LDA) [2] method with Gibbs sampling [28] which is an unsupervised and probabilistic machine-learning topic modeling method that extracts topics from text data. The key assumption behind LDA is that each given text is a mix of multiple topics. The model also tells in what percentage each document talks about each topic. Hence, a topic is represented as a weighted list of words.

We extract ten topics from tweets' text and the LDA returns a set of ten words relating related to each identified topic (but not the title of the topic) (Table 2, Column 2). We then assign appropriate topic titles to each set of words

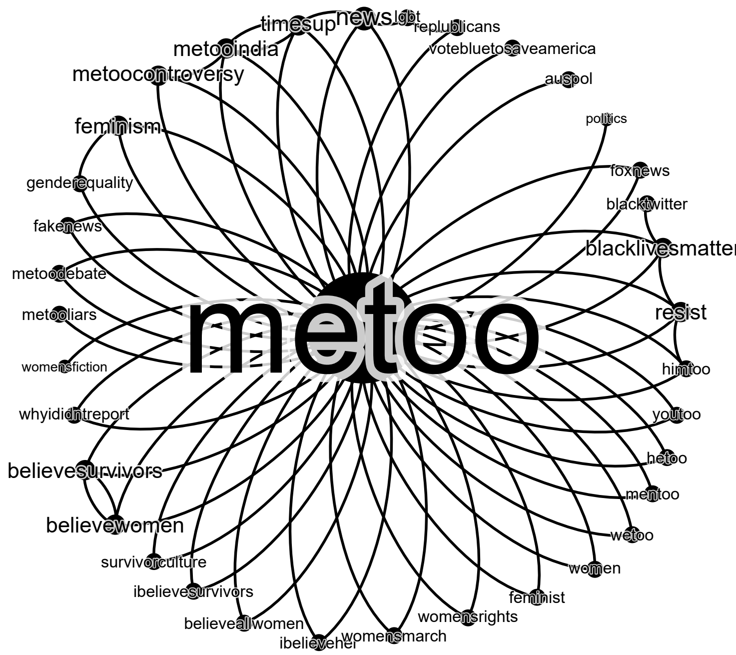


Fig. 1: Using the hashtags of the original tweets, we performed a bi-gram analysis. This identify the most frequent co-occurring hashtags. This makes it convenient to see the hashtags that belongs to each issue.

that closely reflect the topic at an abstract level (Table 2, Column 3). To show the connectivity among various facets of discussion in the *MeToo* movement, we analyze the frequently co-appearing hashtags with *#MeToo* (see Figure 1). Our analysis highlights the hashtags that belong to these hidden facets. For example, *#HimToo*, which represents the *trust deficit among individuals* is a movement against false rape allegations [12].

Our analysis reveals that the *MeToo* movement covers many hard-to-see facets : 1) **People of color:** Individuals are mainly discussing the color facet in SH incidents using the *#MeToo*; 2) **Places of harassment:** Mentioning the probable places of SH and SA incidents; 3) **Trust deficit among individuals:** Individuals discusses the possibility of attracting attention by using false allegations; 4) Use of **hate and offensive vocabulary** in tweets; 5) **Female sexual harassment**; 6) **Role of justice system**; 7) **News and media industry**; 8) **Public speak-outs for survivors**; 9) **Role of world. society, gender and culture**; and 10) **Feminism on Twitter**. In this work, due to space limitation, we concentrate on only five important facets (S.No. 1 to 5) as shown in Table 2.

Type	Words
People of Color	black, white, sexual, racist, woman, support, brown, assault, male, hate
Hate	racist, white, stop, supremacy, human, angry, wrong, rich, color, read
Offensive	shit, fuck, fucking, ass, bitch, bullshit, guys, liar, fake, yall
Domestic	family, house, sexual, support, violence, sister, parents, abuse, harassment, domestic
Work	workplace, harassment, office, era, hire, job, sexual, light, forced, judge
Public	stop, guy, girl, stay, home, day, sexually, feel, night, public
Study	sexual, students, assault, harassment, report, abuse, faculty, victims, violence, survivors

Table 3: Topic Modelling for color, places of assault, hate and offensive vocabulary using LDA.

4.1 People Of Color

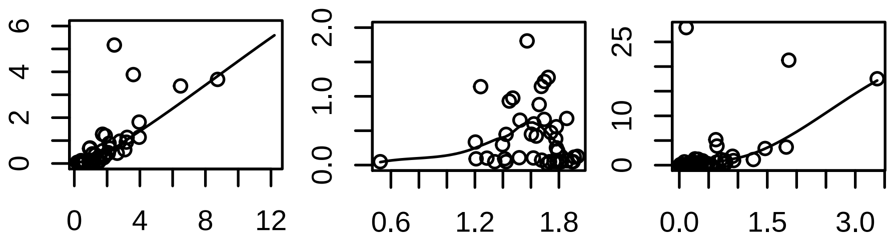
We investigate the color facet in the *MeToo* movement and identify that 2.73% of total tweets belong to color. Tweets containing the hashtags such as *#blacklivesmatter*, *#blacktwitter*, *#blm* etc. along with the *#MeToo* hashtag are labeled under this category.

The topic modeling of tweets listed in the color category (see Table 3, *Type* is *People of Color*) indicates that users are discussing gender and color under this in the *MeToo* movement. We understand that gender and color are sensitive topics and during our analysis, we further observe that discussions over these often lead to hate and offensive vocabulary.

Case study of USA: For further investigation on color category, we study the USA tweets data. We start by comparing the state-wise total, white, and color population percentage [5] with the *MeToo* tweets percentage originated from that state (see Figure 2). We observe a direct relationship between the total population of a state and tweet traffic generated from that state. In other words, higher populated states contribute more to tweeting activity. These findings are further supported by the positive correlation value and p-value (see Table 4).

The relationship between the white population and the tweet traffic generated from that state shows a negative correlation with a low p-value. On the other hand, we observe a direct relationship between the color population and tweet traffic generated from each state. This means that states with higher color population contribute more in tweets belonging to the *MeToo* movement. This is further supported by the positive correlation value. Thus, we can infer that the number of tweets generated and the color population in states of the USA are correlated.

The analysis of color facet of the *MeToo* movement shows that color people are tweeting higher compared to white people during this movement. We further



(a) Total Population (b) White Population (c) Color Population

Fig. 2: Fitting Curve: : Here, x-axis represents state-wise different USA population i.e., in (a) total population, (b) white population, and (c) color population; and y-axis represents tweets traffic.

Population Type	**p-value**	**Corr. Value**	**Corr. Type**
Total population and tweets	0.00124	0.4483	Positive
White population and tweets	0.01642	-0.4312	Negative
Color population and tweets	0.00022	0.5043	Positive

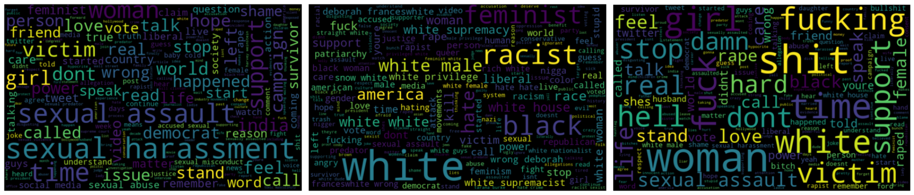
Table 4: USA: Population Vs Tweets (Statistical Data)

notice that discussion over color often leads to the use of hate and offensive vocabulary which is discussed next.

4.2 Hate & Offensive Vocabulary

We identify the *MeToo* tweets that belong to either hate or offensive vocabulary using the HateSonar library from python [9] and find that 10% of the total tweets are either hate or offensive.

For better insights of each category, we perform the topic modelling (see Table 3, *Type* are *Hate* and *Offensive*). For instance, hate category tweets indicate that the hate vocabulary is connected to racism as most frequent words are *racist*, *white* and *black*. Likewise, based on offensive category tweets, we can infer that offensive vocabulary is the sign of strongly impolite and rude behavior. These conclusions are further supported by the word cloud analysis for both hate and offensive vocabulary tweets, as shown in Figures 3b and 3c respectively. Additionally, we observe that the individuals tend to use the offensive vocabulary in case of distrust towards the incidents or survivors (see Table 3, third row).



(a) Overall (b) Hate Speech (c) Offensive Speech

Fig. 3: Users' Vocabulary: Identifying the most frequent words under different vocabulary category.

4.3 Trust and Distrust Among Individuals

Even though *MeToo* movement helps the survivors to share their SH and SA incidents, there is also fear of false allegations among people. A poll by Leanin.org shows that 60% of male managers don't want to mentor women out of fear of a false accusation [20]. On the other hand, according to [4], fears of false accusations are not supported by statistics. This results in some sort of both trust and distrust among people. This has also been observed from the tweets having conflicting hashtags such as *#BelieveWomen*, *#IBelieveSurvivors*, *#IBelieveHer*, or *#BelieveSurvivors* signifying trust category and tweets containing hashtags such as *#metooliars*, *#fakenews*, *#womensfiction*, or *#HimToo*, representing distrust category.

The tweets percentage identified in trust and distrust category are 5.46% and 1.27% respectively. On Twitter, we notice two separate groups of individuals in the *MeToo* movement. First, who trust the survivors; and others who show distrust towards the incidents shared by survivors.

4.4 Places Of Harassment

According to the survey by [7], the majority of women (66%) had been sexually harassed in public spaces, 38% of women experienced it at the workplace, 35% had experienced it at their residence. However, workplace and domestic experiences are more likely to be assaults and the "most severe forms" of harassment [7]. Inspired by these studies, we annotate the tweets into four places of harassment categories, (1) Domestic, (2) Workplace, (3) Public place, and (4) Educational institutions. We use specific keywords to annotate these tweets into different categories. The complete list of keywords in each category is shown in Table 5. The percentage of total tweets identified in each category are as follows: *domestic* (3.23%), *work* (3.42%), *public* (0.90%) and *study* (1.40%). We can infer that under the *#MeToo*, domestic and work place SH incidents are higher compared to the educational institutions and the public places.

The topic modeling analysis of tweets for each mentioned places of harassment categories (see Table 3, the last four rows) provide collective insights. For

Type	Keywords
Domestic	home, parent, parents, friend, legal guardian, domestic, family, house, residence, mother, father, single parent, lone parent, brother, sister, step brother, step sister, stepmother, stepfather, adoptive mother, adoptive father, apartment, household
Work	workplace, work place, work, work environment, office, employment, interview, employer, employee, job, business, organization, working, factories, co-worker, client, supervisor, hire, company, colleague, workmate
Public	park, bus, public place, theater, stranger, train, restaurant, bar, bus stop, public park, mall, street
Study	school, college, student, academic, educational, teacher, professor, secondary school, university, faculty, study, studies, classmate, friend

Table 5: List of keywords used to annotate tweets into various categories of places of harassment.

instance, from workplace violence tweets, we can infer that workplace SH incidents often occur during recruitment or interview processes. This also indicate that disclosing SH events in the office environment may lead to the victim being judged. Similarly, from public place tweets, we may infer that women feel unsafe in public places.

In this section, we explore the extracted hidden facets of the *MeToo* movement in detail using tweets text. Our results show that people of color are reporting higher SH incidents. We also find that discussion about color often leads to the use of hate and offensive vocabulary. This further follows by the distrust among individuals towards the incidents or survivors of SH. Next, we study the user interactions with respect to these facets in the *MeToo* movement.

5 Users' Communities And Leaders

To understand the topic distribution across various users of our dataset, we employ social network analysis technique. We build the directed "retweet" network among users: an edge ($u \longrightarrow v$) indicates that user u retweet user v (see Figure 4). The descriptive statistics of the retweet network is provided in Table 6. The lower value of the average clustering coefficient (Average C.C.) and edge density, can be used to infer that the network is sparse. This further indicates that the network is spread out, which is further confirmed by a large diameter. From the values of weakly connected components (WCC) and the number of components, and the average path length we can conclude that there are a large number of small communities.

In Figure 4, users are grouped into communities based on Louvain community detection algorithm [3] and for better representation each community is color-coded. We observe that users discussing the similar facets form a strong

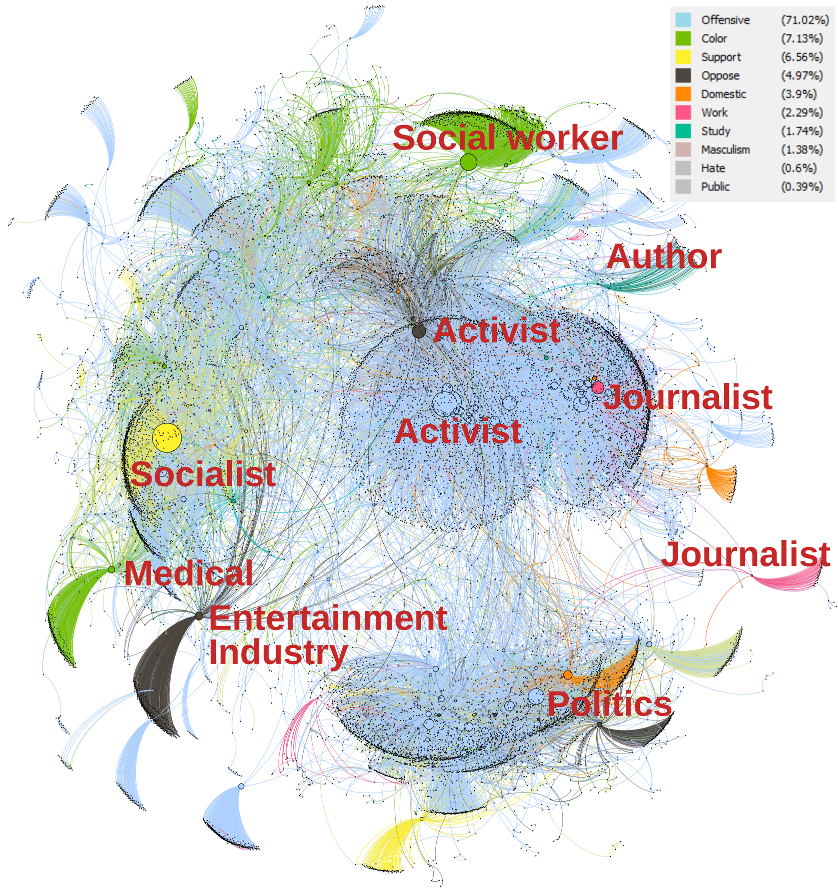


Fig. 4: Leaders' profession and user-communities.

community. For example, users discussing the *color* facets are shown in *green* and they forms a strong community. The legend in Figure 4, provide the complete list of colors assigned to individual users that belongs to various facet of the *MeToo* movement.

Next, we identify the leaders of these communities. Our definition of leaders relies on the fact that they are often retweeted a relatively higher number of times. We employ the well-known degree centrality algorithm to identify them and are shown with relative bigger node size in the Figure 4. To study leaders in more detail, we explore their professions. We check their publicly available information such as profile description, tweets' frequency and contents. We observe that the content from activists, journalists, authors, singers, and media people are highly appreciated (i.e., retweet) during the *MeToo* movement on Twitter.

Parameter	Value
Number of nodes	846,102
Number of edges	2,223,281
Average clustering coefficient	0.0946
Size of weak and strong clustering coefficient	809,979
Number of triangles	5,149,422
Number of components	14,870
Edge density	6.2e-6
Average path length	8.51
Diameter	30

Table 6: Users Network Statistics.

6 Conclusion

The purpose of the *MeToo* movement is to empower survivors by bringing them together and share their experiences. People from around the world are putting their efforts irrespective of gender, color, or culture to fight against SH and SA. However, the *MeToo* movement is not just about sharing SH and SA incidents but rather it is about bringing the change in the society and this change requires awareness towards different causes of SH and possible solutions to restrict these incidents in the future.

This study reveals these hidden facets of the *MeToo* movement and highlights that (1) people of color report a higher number of SH and SA incidents; (2) discussion about color often leads to the use of hate of offensive vocabulary; (3) presence of distrust among individuals towards the incidents or survivors of SH; (4) domestic and workplace SH incidents are drastically high; (5) users discussing a similar alignment forms a strong community; and (6) the content from activists, journalists, and media people are highly appreciated (i.e.,retweet) during the *MeToo* movement on Twitter.

The major limitation to this work is that our analysis may not be generalized to other similar movements such as *#genderequality* which is a feminism movement.

Our future work would consider several important directions, such as to determine the effect of users' response and media (such as images and videos) in such movement. First, we plan to investigate how users respond to positive and supporting tweets compared to abusive and offensive tweets. For instance, abusive and offensive tweets may cause users to leave the discussion otherwise, they wouldn't have. On the other hand, positive and supporting tweets may encourage more survivors to share their incident(s), which leads to a healthy discussion. Also, nowadays, images and videos are a significant portion of the data generated on social media sites. Hence, we plan to analyze them in-depth for the understanding of such movements.

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