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#NotOkay: Understanding Gender-Based Violence in Social Media

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Abstract

Gender-based violence (GBV) is a global epidemic that is powered, in part, by a culture of silence and denial of the seriousness of its repercussions. In this paper, we present one of the first investigations of GBV in social media. Considering Twitter as an open pervasive platform that provides means for open discourse and community engagement, we study user engagement with GBV related posts, and age and gender dynamics of users who post GBV content. We also study the specific language nuances of GBV-related posts. We find evidence for increased engagement with GBV-related tweets in comparison to other non-GBV tweets. Our hashtag-based topical analysis shows that users engage online in commentary and discussion about political, social movement-based, and common-place GBV incidents. Finally, with the rise of public figures encouraging women to speak up, we observe a unique blended experience of non-anonymous self-reported assault stories and an online community of support around victims of GBV. We discuss the role of social media and online anti-GBV campaigns in enabling an open conversation about GBV topics and how these conversations provide a lens into a socially complex and vulnerable issue like GBV.

Introduction

Gender-based violence (GBV) is one of the most prevalent human rights violations in the world. GBV is commonly defined as "*any form of violence that results in, or is likely to result in, physical, sexual or psychological harm or suffering to women, including threats of such acts, coercion or arbitrary deprivations of liberty, whether occurring in public or in private life*" (United Nations 1993). According to the United Nations Population Fund (UNFPA), worldwide, one in three women will experience physical or sexual abuse in her lifetime (UNFPA 2016). Collected data reveal that GBV is pervasive across all social, economic and national strata (United Nations 2016; World Health Organization 2010).

Vital to the design of social and economic policies that target GBV at its roots is the availability of data. The analysis of GBV through data is not only crucial to understanding GBV patterns, it is critical to measuring community-wide engagement, public opinion, and expression sensing as well as designing data-driven policies for raising awareness (Esty and Rushing 2007). Despite the significant on-going effort into gathering GBV data (GBVIMS 2016), many specifics of GBV remain a grey zone due to a variety of reasons including victim blaming, and shamefulness (Buchbinder and Eisikovits 2003), among others.

Within the past decade, social media has become a platform for social activism movements including *Black Lives Matter* (#blacklivesmatter) for racial equality and *Love Wins* (#lovewins) for marriage equality; the same can be said for GBV-based context. With 313 million active users, 1 billion monthly visits to sites with embedded tweets, and 79% of accounts outside the US, Twitter[1] is a pervasive open platform that facilitates a unique lens into GBV, both in terms of victims sharing their stories as well as the promotion of GBV, and subsequent reactions, both positive and negative.

We are driven by Twitter as an infrastructure for social activism to study characteristics of online GBV. We are also inspired by recent events across the globe that led to the movement of GBV victims sharing their stories on the Twitter platform. For instance, as recently as October 2016, Canadian author and social media blogger Kelly Oxford started a conversation on Twitter encouraging women to share their first assault experiences, as shown in Figure 1. The response was overwhelming; she reported that she received 1 million tweets in one night with a minimum rate of 50 tweets per minute (CNN 2016).

Through social media, we can thus study aspects related to self-reported stories, GBV news shares and user participation in the discussion. Our research seeks to understand user engagement with GBV posts, how users shape their GBV stories and the role of age and gender in online GBV contexts. To do so, we mine approximately 300,000 Twitter tweets, between April and November 2016.

Specifically, we seek to answer the following research questions using our datasets:

- *RQ 1:* What are the characteristics of user engagement with GBV stories?
- *RQ 2:* How do GBV tweet characteristics and content vary based on user demographics such as age and gender?
- *RQ 3:* How do authors present GBV stories?

[1]https://about.twitter.com/company

Figure 1: Kelly Oxford invites women to share sexual assault stories on Twitter.

Previous work has explored the use of misogynistic language in Twitter (Bartlett et al. 2016) and investigated the correlation between misogynistic content in Twitter (Fulper et al. 2014) and the FBI Uniform Crime Reports[2] for rape statistics in 2012. While the work in (Purohit et al. 2015) and (Karuna et al. 2016) examines GBV properties across geographic locations and anti-GBV campaigns in Twitter, respectively, online GBV computational studies through social media is still in its initial forms. Our work represents a first attempt to characterize user engagement, author story representation, and author demographics in the context of GBV in social media.

Our results show that social media is a key enabler for people to discuss GBV issues – this is apparent by the large number of self-reported stories and the sharing of news domains that host GBV-related stories. We also find, on average, higher engagement associated with GBV posts in comparison with generic tweets and that female participation is higher for ages less than 30 while male participation is higher for ages above 30. Finally, we show that GBV hashtags inspire self-expression and communal coping through sharing and support.

Background and Related Work

Our work is best understood in the realm of the following theories:

Social Movements

Looking at GBV as a global crisis, anti-GBV campaigns can be viewed as social movements to increase awareness against GBV and provide venues for people from different backgrounds to participate in the conversation. In 2016, the US White House's #StateOfWomen[3] summit deliberated violence against women under the umbrella of gender equality issues. UN Women aimed to increase the engagement of males through the #HeforShe[4] campaign against inequalities faced by women. These anti-GBV campaigns, as well as others such as ItsOnUs[5], used hashtags on social media websites to spread the word globally. Use of social media by individuals and organizations to promote collective action and engagement is not new. Prior work that has extensively studied social movements in social media includes studies of the "Black Lives Matter" movement for racial equality (De Choudhury et al. 2016; Olteanu, Weber, and Gatica-Perez 2016) and revolutions that helped shape the Arab Spring (Lotan et al. 2011; González-Bailón et al. 2011). While these studies focus on issues other than GBV, some of the research questions regarding users' topical engagement, demographics and attitude remain equivocal in the context of GBV.

Close to our work is the work of (Purohit et al. 2015; Karuna et al. 2016). Purohit et al. used a key phrase based approach to gather GBV tweets over a period of 10 months and used a mixed methods approach (Creswell 2013) to focus on analyses such as volume, gender and language indicators. Our work differs in that we scrutinize user and tweet related key aspects such as common demographics, tweet visibility, and GBV story representations. The work in (Karuna et al. 2016) examines the communities of three anti-GBV campaigns: #ItsOnUS, #StateOfWomen and #HeForShe and their community overlap. While we take these hashtags into consideration, our analysis complements this work by covering a broader set of hashtags. Our diverse hashtag set includes, among campaign related hashtags, ones that involve sharing personal experiences such as #NotOkay, #WhyIStayed and #BeenRapedNeverReported and others that aim to discuss and answer GBV related reality issues such as #WhyWomenDontReport, #MaybeHeDoesntHitYou, and #IBelieveSurvivors.

Influence

Social contacts in the physical world (de Sola Pool and Kochen 1978; Domingos and Richardson 2001) or in social media (Cha, Mislove, and Gummadi 2009; Hill, Provost, and Volinsky 2006) can have a strong influence on the attitude of individuals. An extensive body of literature has studied how social media's exposure can influence an individual's psychological states (Bollen et al. 2011; Dodds et al. 2011; Coviello et al. 2014; Fan et al. 2014b). Other work has explored the influence of content creation on social media attitude, such as retweeting, replying or favoriting, for example in the context of the Twitter platform. For instance, Leavitt et al. 2009 classified user's influence into two types: content-based and conversation-based. This work concluded that influential people such as celebrities were better at starting conversations on social media while news outlets content resulted in more retweets.

The ultimate form of influence is to promote collective action via social networks; this was visible in the Black Lives Matter (BLM) movement (De Choudhury et al. 2016) and the Arab Spring (Lotan et al. 2011). On the theoretical end of studying influence and factors that promote users to endorse certain campaigns, points of view or products, lie the theories of Influence Maximization and Contagion. Influence Maximization is the problem of finding a set of nodes in a network that maximizes the spread of an idea or campaign. Greedy algorithms and heuristics that were

[2]https://ucr.fbi.gov/crime-in-the-u.s/2012/crime-in-the-u.s.-2012

[3]The United State of Women: http://www.theunitedstateofwomen.org/

[4]UN Women HeForShe campaign: http://www.heforshe.org/en

[5]http://itsonus.org/

GBV category:	Physical Violence (PhysViol)	Sexual Violence (SexViol)	Harmful Practices (HarmPrac)
Key phrases	woman/women/girl/female beat up	sexual assault	child/children/underage/forced marriage
	woman/women/girl/female acid attack	sexual violence	sex/child/children trafficking
	woman/women/girl/female violence	woman/women/girl/female harass	woman/women/girl/female trafficking
	woman/women/girl/female punched	woman/women/girl/female attacked	*child molestation/bride/sex/*
	woman/women/girl/female attacked	boyfriend/boy-friend assault	*child violence/abuse/bullying/beat*
	gender/domestic violence	stalking woman/women/girl/female	*spouse abuse*
	intimate partner violence	groping woman/women/girl/female	*sex/women/forced slave*
	physical abuse/violence	*sexual/rape victim*	*female genital mutilation (fgm)*
		gang rape	*early marriage*
		victim blam	*pedophilia*
		sex predator	*human trafficking*
		woman/women/girl/female forced	*woman abuse*

Table 1: Key phrases used to identify GBV tweets. Newly identified key phrases are italicized.

#notokay: author Kelly Oxford invites women to share assault stories on Twitter (2016)
#whyistayed: users discuss their experience of domestic violence in the wake of the Ray Rice abuse incident (2014)
#yesallwomen: users share stories of misogyny and violence against women following the Isla Vista killings (2014)
#whywomendontreport: Vox correspondent Elizabeth Plank asked her Twitter followers why women do not report sexual assault (2016)
#beenrapedneverreported: Montgomery and Zerbisias co-created the hashtag to tweet support for the women who alleged they were assaulted by former CBC radio host Jian Ghomeshi (2014)
#ibelievesurvivors: brings up the issues around victim shaming and women reporting sexual assault allegations to police (2016)
#itsonus: hashtag associated with movement dedicated to changing the culture around campus sexual assault (2014)
#stateofwomen: hashtag associated with the White House summit discussing challenges that face women (2016)
#heforshe: UN's women campaign for gender equality aiming to engage men and boys as agents for change (2014)
#maybehedoesnthityou: writer and artist Zahira Kelly used Twitter to publicly share her emotional abuse experience (2016)

Table 2: Hashtags used in the context of GBV.

proposed to solve this problem were studied in (Kempe, Kleinberg, and Tardos 2003; Leskovec et al. 2007; Chen, Wang, and Yang 2009). The Contagion theory aims to explain how ideas spread across human social networks. Granovetter 1978 explains that people will engage in a certain behavior by contagion if the number of people in the group who adopt that behavior exceeds a certain threshold. In the context of social networks, (Romero, Meeder, and Kleinberg 2011) found that political and idiom tags had a higher rate of contagion growth than other random topics on Twitter. Other work supported the contagion theory for petition virality (Goel et al. 2015) and showing support for same-sex marriage by overlaying profile pictures in Facebook (State and Adamic 2015). To understand how to maximize GBV visibility, we explore how users engage in the context of GBV in Twitter. We examine both favorite rate and retweet rate of original GBV content on Twitter and compare these metrics for different forms of GBV as well as comparing GBV tweets with generic tweets.

Data and Methods

Social Media Data

We collected data from Twitter via two methodologies:

(1) Key phrase-based dataset (GBV-KP-1%*)*: For this dataset, we used Twitter's Streaming API to procure a 1% sample of Twitter's public stream. We then applied our own filtering process by using the key phrases in Table 1 to identify relevant GBV tweets. Specifically, we first used the key phrases identified by UNFPA domain experts in (Purohit et al. 2015). Purohit et al. analyze a dataset of 13.9 million tweets from Jan 1st to Oct 31st, 2014 in non-uniform time slices and differentiate between three categories of GBV: Physical Violence, Sexual Violence, and Harmful Practices. In our work, we adopt the same categorization scheme. Upon examining the results of our initial crawling attempt, we excluded a set of key phrases that resulted in irrelevant content. These key phrases contained keywords that were used colloquially in discourse and contexts that were extraneous to GBV. For the Physical Violence category, we excluded the key phrases containing the words dragged, kicked, beaten, and burn. For the Sexual Violence category, we excluded the word "rape" but replaced it with the more specific "rape victim" and "gang rape" key phrases. In the analysis conducted in (Bartlett et al. 2016), it has been shown that the word "rape" appeared in serious/news contexts 40% of the time and 60% in other types of discourse including casual and metaphor categories. Following a snowball approach and multiple crawling phases, we were able to identify 35 unique key phrases. Table 1 encompasses both UNFPA key phrases and our newly-identified key phrases.

(2) Hashtag-based datasets: For a more detailed study of recent events, we include two other datasets based on the 10 hashtags specified in Table 2. For the first dataset (*GBV-HT-*1%), we filtered the 6-month 1% sample of Twitter's public stream using these hashtags. Table 2 depicts the used hashtags, the initial incidents that sparked their creation, and the year they first appeared. For the hashtag #notokay, we only include tweets that also contain the mention @kellyoxford in order to exclude tweets that mention the hashtag but discuss issues other than GBV.

Dataset	Time Range	Tweets	Users	Content creators
GBV-KP-1%:	04/13/16-10/13/16			
PhysViol		34,380	31,085	8,574
SexViol		93,567	82,132	18,160
HarmPrac		108,822	92,499	21,925
GBV-HT-1%	04/13/16-10/13/16	6,454	5,999	1,602
GBV-HT-Comp	10/26/16-11/26/16	58,908	34,450	35,490
General-1%	10/26/16-11/26/16	33,055,294	11,394,125	2,572,617

Table 3: Descriptive statistics of GBV Twitter datasets.

For a more comprehensive[6] hashtag-based dataset (*GBV-HT-Comp*), we use Twitter's public streaming API[7] to collect tweets from October 26th to November 26th, 2016 that contain the indicated hashtags. Because Twitter's Streaming API cannot be used to track certain hashtags, we specify the hashtags as keywords (e.g. notokay), then we apply a string matching approach to identify the # symbol followed by the hashtag string (e.g. #notokay).

To provide a larger context for interpretation within our experiments, we compare the *GBV-HT-Comp* dataset with a 1% sample of all tweets (including non-GBV tweets) using a 1-month dataset (*General*-1%) spanning the same time period (10/26/16 - 11/26/16). We filter all non-English tweets from our datasets. We also apply preprocessing to eliminate repeated tweets and tweets from authors with zero followers. Table 3 constitutes an overview of the time-span covered by each dataset, the number of tweets, and number of unique users and content creators.

Measures

In our investigation, we adopt several measures based on prior work in order to answer the proposed research questions. For content sharing and engagement, we examine multiple metrics including favorite rate, retweet rate, and number of tweets containing links and media. To identify influential topics, we look at the prevalence of hashtags. Focusing on the actual nature of GBV stories and how authors represent GBV, we use the psycholinguistic lexicon LIWC (Chung and Pennebaker 2007) to measure interpersonal awareness, affect, and emotional expressions. In our analysis, we differentiate between the notions of *perceived vs actual user characteristics*. When we look at account characteristics of content creators or consumers, we study the perceived account characteristics (e.g. gender and age) that are visible in their account. Nilizadeh et al. 2016 studied the association between perceived gender and measures of online visibility. Recent work that investigates the inference of actual user characteristics from online content in social networks, aka *user profiling*, include age, gender, and occupation estimation in (Zhang et al. 2016; Hu et al. 2016; Perozzi and Skiena 2015; Marquardt et al. 2014). We specifically study user perceived age and gender using an automatic facial feature recognition service "Face++" (Fan et al. 2014a).

[6] as opposed to the 1% sample

[7] Twitter's public Streaming API https://dev.twitter.com/streaming/public

Analysis

RQ1: User engagement with GBV tweets

To answer RQ 1, we begin by exploring the engagement of users with GBV content on Twitter. In particular, we examine metrics related to favoriting and re-sharing a tweet (retweeting). In Twitter, once a user favorites a tweet, that tweet is automatically archived in the user's profile for the user and their network to read later. Retweeting is the act of resharing content with followers of the user. Retweets do not necessarily indicate content endorsement but suggest content to be viewed by the retweeter's network. Retweets provide a powerful tool for tweets to be shared beyond the content creators' network of followers (Twitter 2016). As a user's follower network grows, so does the visibility of their content on Twitter. To incorporate this effect, we normalize favorite and retweet counts by the size of a user's follower network. We, therefore, compute two metrics for each tweet, favorite rate and retweet rate, which are defined as follows:

$$\begin{aligned} Favorite\ rate\ (FR) &= \frac{Favorite\ count}{Followers\ count} \\ Retweet\ rate\ (RR) &= \frac{Retweet\ count}{Followers\ count} \end{aligned} \tag{1}$$

where favorite count and retweet count indicate how many times a tweet is favorited and retweeted, respectively. We note that favorite count and retweet count are a function of the tweet while the followers count depends on the user's network. The content captured in our datasets falls into one of three categories: original, retweet, and reply. If a retweet exists, this suggests that the retweet count for the original tweet reflects the resharing accordingly. For this analysis, we thus consider only original tweets in our datasets. Since the datasets used in our analyses were gathered using the Twitter streaming API at the time of their creation, the corresponding favorite and retweet counts associated with each tweet's body of information were zero-valued. In order to accurately capture the eventual favorite and retweet counts, we queried the Twitter API again at a later time[8] to allow user engagement with tweets. Table 4 depicts the number of original tweets investigated for each dataset, favorite count and rate, and retweet count and rate descriptive statistics.

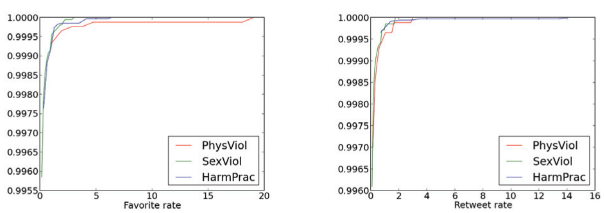
We are particularly interested in exploring two questions. First, *do different types of GBV tweets exhibit different engagement patterns?* and second, *how does engagement with a GBV tweet differ from a generic non-GBV tweet?*

Engagement based on tweet GBV category. To answer the first question, we study PhysViol, SexViol, and HarmPrac categories in the *GBV-KP*-1% dataset. All three categories were collected over the same six-month duration, from April 13th to October 16th, 2016. We compute the Favorite rate and Retweet rate for the three categories of GBV tweets and plot the corresponding Cumulative Distribution Functions (CDF) in Figure 2. To determine whether there are significant differences between the three datasets, we used Kruskal-Wallis H test for the Favorite rate and the

[8] in December 2016, resulting in a minimum of one month and a maximum of eight months of interaction

Dataset	Engagement stats
GBV-KP-1%: *PhysViol*	**Original tweets:** 8,711 **Favorite count:** Min = 0, Max = 1394, $\mu = 2.39$, $\sigma = 28.16$ **Favorite rate:** Min = 0, Max = 19, $\mu = 0.0067$, $\sigma = 0.21$ **Retweet count:** Min = 0, Max = 2282, $\mu = 2.14$, $\sigma = 31.5$ **Retweet rate:** Min = 0, Max = 3, $\mu = 0.0030$, $\sigma = 0.046$
SexViol	**Original tweets:** 20,999 **Favorite count:** Min = 0, Max = 4844, $\mu = 3.74$, $\sigma = 64.02$ **Favorite rate:** Min = 0, Max = 3, $\mu = 0.0042$, $\sigma = 0.0486$ **Retweet count:** Min = 0, Max = 2816, $\mu = 2.79$, $\sigma = 42.37$ **Retweet rate:** Min = 0, Max = 1.75 , $\mu = 0.0021$, $\sigma = 0.0302$
HarmPrac	**Original tweets:** 35,315 **Favorite count:** Min = 0, Max = 1497 , $\mu = 1.45$, $\sigma = 15.48$ **Favorite rate:** Min = 0, Max = 6.33, $\mu = 0.0043$, $\sigma = 0.0652$ **Retweet count:** Min = 0, Max = 1168, $\mu = 1.09$, $\sigma = 11.64$ **Retweet rate:** Min = 0, Max = 14.07, $\mu = 0.0022$, $\sigma = 0.08$
GBV-HT-Comp	**Original tweets:** 13,871 **Favorite count:** Min = 0, Max = 3447, $\mu = 6.16$, $\sigma = 59.65$ **Favorite rate:** Min = 0, Max = 21.75, $\mu = 0.0191$, $\sigma = 0.2466$ **Retweet count:** Min = 0, Max = 1351, $\mu = 2.81$, $\sigma = 23.44$ **Retweet rate:** Min = 0, Max = 17.75, $\mu = 0.0071$, $\sigma = 0.1581$
General-1%	**Original tweets:** 82,083 **Favorite count:** Min = 0, Max =29819, $\mu = 2.62$, $\sigma = 111.24$ **Favorite rate:** Min = 0, Max = 12, $\mu = 0.0056$, $\sigma = 0.0786$ **Retweet count:** Min = 0, Max = 7055, $\mu = 1.25$, $\sigma = 37.4$ **Retweet rate:** Min = 0, Max = 8.69 , $\mu = 0.0021$, $\sigma = 0.05432$

Table 4: Descriptive statistics for engagement with GBV posts.

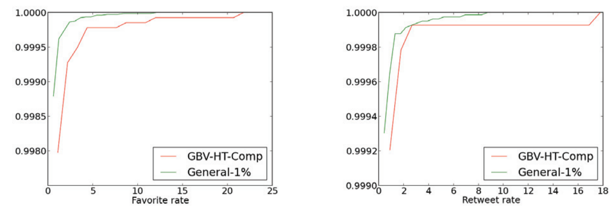


(a) (b)

Figure 2: Cumulative distribution associated with (a) Favorite rate and (b) Retweet rate for three categories of GBV.

Retweet rate. The test statistic for the Favorite rate was $H = 73.8$ with p-value $< .001$ and for the Retweet rate was $H = 75.4$ with p-value $< .001$. On average, PhysViol tweets were favorited approximately $1.6\times$ more than SexViol and HarmPrac tweets ($\mu_{FR-PhysViol} = 0.0067$ vs $\mu_{FR-SexViol} = 0.0042$ and $\mu_{FR-HarmPrac} = 0.0043$). We also noted that the probability of a tweet's favorite count extending beyond network size (i.e. $P(FR > 1)$) is larger for PhysViol tweets and approximately the same for SexViol and HarmPrac tweets. Following the same pattern, PhysViol tweets were retweeted on average $1.4\times$ more than SexViol and HarmPrac tweets ($\mu_{RR-PhysViol} = 0.0030$ vs $\mu_{RR-SexViol} = 0.0021$ and $\mu_{RR-HarmPrac} = 0.0022$); $P(RR > 1)$ is larger for PhysViol tweets and approximately the same for SexViol and HarmPrac tweets.

Engagement with GBV tweets vs General tweets. To answer the second question, we study the *GBV-HT-Comp* dataset and compare it with a random sample of $82,083$ original tweets from the *General*-1% dataset from the same time period. We plot the CDF for Favorite rate and Retweet rate for both datasets in Figure 3. To determine if there



(a) (b)

Figure 3: Cumulative distribution associated with (a) Favorite rate and (b) Retweet rate for GBV tweets versus General tweets

are significant differences between the two distributions, we conduct the Wilcoxon-Mann-Whitney test for the Favorite rate and Retweet rate. The test statistic for the Favorite rate was $U = 43.7$ with p-value $< .001$ and for the Retweet rate was $U = 47.3$ with p-value $< .001$. On average, a GBV tweet was favorited $3.41\times$ more than a General tweet ($\mu_{FR-GBV-HT-Comp} = 0.0191 > \mu_{FR-General-1\%} = 0.0056$). We also noted that the probability of a tweet's favorite count extending beyond network size (i.e. $P(FR > 1)$) is larger for GBV tweets than General tweets. A similar result was found for the Retweet rate ($\mu_{RR-GBV-HT-Comp} = 0.0071 > \mu_{FR-General-1\%} = 0.0021$) and $P(RR > 1)$ is larger for GBV tweets.

RQ2: Age and gender variables for users in the GBV context

We utilize descriptive statistical analysis to discover relationships among tweets, gender, and age collected from the Twitter REST API and the Face++ API. In this experiment, we combine the hashtag-based datasets, GBV-HT-1% and GBV-HT-Comp, into one dataset (*HT*) since the emphasis of the experiment is to identify demographic variables for users regardless of time span. For all types of tweets (original, reply, or a retweet), we identify Twitter user IDs associated with each tweet and query the Twitter REST API to extract the user's profile picture url. We then feed the picture's url to the Face++ API, which predicts the demographic information of a given photo (e.g. age, gender, and race). Upon compiling the demographic information of each user, Face++ returns a confidence level for its detection. We omit any results with a confidence level below 95% (21.7% of the total queries). This results in data for 9,837 users for PhysViol, 7,373 users for SexViol, 10,591 users for HarmPrac and 12,996 for HT.

We plot the age-gender distribution for the combined datasets PhysViol, SexViol, and HarmPrac in Figure 4. Figure 4 shows that highest participation is in the age range 20-29, followed by 30-39, and then 10-19. We list the percentages of female vs male participation across age ranges in Table 5. We note that female participation is dominant across age ranges ≤ 9, 10-19 and 20-29, and decreases as age increases, while male participation dominates above 30, increasing with age[9]. The same observations were consis-

[9]We show the results for ages 0-9 despite the fact that the ma-

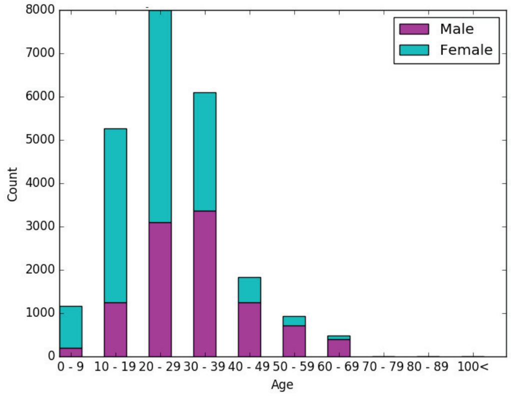


Figure 4: Breakdown of users by perceived age and gender for PhysViol, SexViol and HarmPrac datasets.

tent across individual datasets: PhysViol, SexViol, HarmPrac, and HT; we omit the results due to space limitations.

Dominant female participation in the range of [55.76%-100%] was also observed for all the hashtags in Table 2. We study gender participation for different types of tweets (original, retweet and reply) across all datasets and note that female participation with original content is dominant across all datasets, ranging from [55%-68.21%], and for retweeting ranging from [56%-69.5%]. In the case of replies, male responses dominate in the HarmPrac dataset with 55% while females dominate in PhysViol, SexViol, and HT in the range [53.5%-64.2%]. Higher female participation was also noted in (Karuna et al. 2016) in the context of anti-GBV activism.

Despite the previous results, there remains a need to provide a more comprehensive gender breakdown with respect to the specific context of a GBV tweet. For instance, do women provide more content focusing on raising awareness of GBV? Do women provide more content that reports GBV events on behalf of themselves or others? Are men and women equally likely to tweet support for GBV victims? Our future work will more deeply correlate content type with content creator demographics.

Age range	Female (%)	Male (%)
≤ 9	82.53	17.47
10-19	76.32	23.68
20-29	61.19	38.81
30-39	44.95	55.05
40-49	31.44	68.56
50-59	22.57	77.43
60-69	16.32	83.68

Table 5: Percentage of female and male participaton across age ranges in PhysViol, SexViol and HarmPrac.

jority of the actual users are not likely to be in this age range. Upon investigation, we found this age range to include users that have cartoon pictures as profile pictures or photos of their children as their account profile photo.

Dataset	One or more url (%)	# Unique domains
GBV-KP-1%:		
PhysViol	41.04	3,247
SexViol	44.15	5,219
HarmPrac	58.21	12,491
GBV-HT-1%	34.75	385
GBV-HT-Comp	37.36	990

Table 6: Descriptive statistics of url usage in GBV tweets.

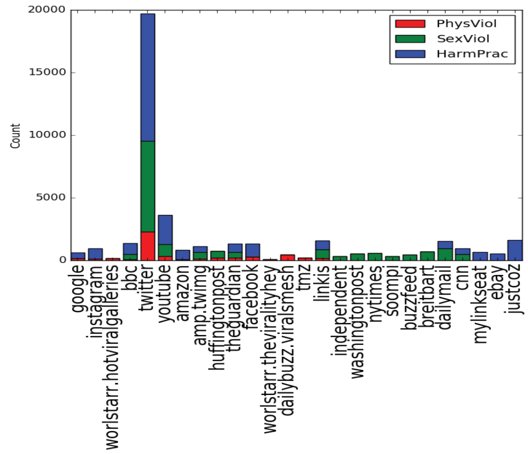
RQ3: GBV story representation on Twitter

In order to understand GBV story representation, we examine three different parameters: the use of embedded urls, topics of interest by looking at viral hashtags, and the common linguistic properties in tweets.

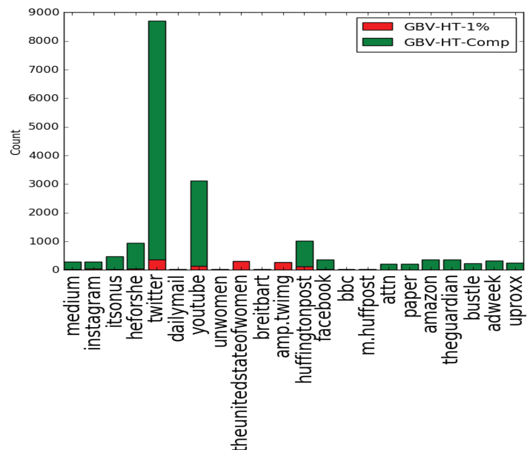
Shared content via url usage. Since a tweet is bound to a maximum of 140 characters, Twitter users commonly embed urls that redirect readers to relevant content. To more deeply understand GBV tweets, we quantify the usage of urls and examine the top visited domains in our datasets. We parse the tweet text to extract urls and perform a GET request with as many redirections on each url as needed until the last destination is hit. Upon reaching the target url, we capture subdomains and domains. Table 6 depicts the percentage of tweets containing one or more embedded urls and the number of unique domains for each dataset. The dataset with the lowest percentage of tweets containing urls was GBV-HT-1% with a percentage of 34.75%; the dataset with the highest number of urls was HarmPrac with 58.21%. On average, 43.7% of tweets across all datasets contained one or more url.

Next, we examine the top 15 domains for each dataset. We group the results for PhysViol, SexViol and HarmPrac datasets in Figure 5(a) and the results for GBV-HT-1% and GBV-HT-Comp, since they cover the same set of hashtags, in Figure 5(b). Figure 5 shows a large presence of social media websites (e.g. Twitter, Instagram, Facebook, and Youtube). Upon inspection of the tweets, we found out that users often reference other GBV content, such as a status on Twitter, a Facebook post, a Youtube video or an Instagram picture. We also note the huge presence of news and blog websites that share full GBV stories. Examples of news domains include BBC, Independent, Washington Post, New York Post, CNN, Daily Mail, and The Huffington Post. Across the blog websites, the most frequently occurring were medium, bustle (offering online content for women and by women) and adweek. Since some hashtags were related to anti-GBV campaigns, domains referencing these initiatives, were also encountered e.g., heforshe.org, itsonus.org, and theunitedstateofwomen.org.

Relationship to on the ground realities. To identify current on the ground topics related to GBV, we investigate the trending hashtags for each dataset which act as topical labels to their tweets. Table 7 depicts the top 10 hashtags for each dataset. We discern four types of hashtags: *social-movement*, *political*, *violence incidents*, and *generic* hashtags. Social-movement hashtags include #ghanaendsdomesticviolence, #youoksis, #mcug16, #internationalmensday, #heforshe and the hashtags #shiftyourperspective and



(a)



(b)

Figure 5: Distribution of top 15 urls used across (a) PhysViol, SexViol and HarmPrac datasets and (b) GBV-HT-1% and GBV-HT-Comp.

#turnstwo which are specifically associated with #heforshe. The hashtag #ghanaendsdomesticviolence discusses the launch of the Government of Ghana's National Survey on Domestic Violence as a mean of advancing its gender equality agenda. The goal of the #youoksis movement is to inspire people of both genders to intervene with street harassment situations by engaging with the victim of said harassment. The hashtag #turnstwo celebrates the second anniversary of the launch of the HeForShe movement, while #shiftyourperspective is also associated with tweets asking males and boys to change their perspective as a part of the HeForShe campaign. Political hashtags are also observed in our datasets since the time duration of our datasets coincided with the 2016 US Presidential elections. These include the hashtags #trump, #tcot, #trumptapes, #hillary, #iamwithher, #trump2016, and #americafirst. These hashtags were typically used to talk about sexual assault allegations in the political context. Hashtags concerning violence include #ripamy, #justice4cindy, #terencecrutcher, #brockturner. These incidents cover a range of types of violence including physical violence, domestic abuse, and rape. Other hashtags encountered cover the broader scope of GBV by opening a discussion about #domesticviolence, #violenceagainstwomen, and #womenrights, among others.

GBV-KP-1%

- PhysViol: ripamy, maybehedoesnthityou, ghanaendsdomesticviolence, youoksis, violence, justice4cindy, terencecrutcher, violenceagainstwomen, domesticviolence, news
- SexViol: trump, tcot, trumptapes, brockturner, sexualassault, hillary, sexualviolence, imwithher, trump2016, news
- HarmPrac: child, endviolence, endfgm, endchildmarriage, sex, fgm, abuse, nsfw, childabuse, humantrafficking

GBV-HT-1%: americafirst, tcot, itsonus, notokay, whatweshare, heforshe, shiftyourperspective, turnstwo, rape, yesallwomen

GBV-HT-Comp: globalgoals, itsonus, notokay, womensrights, internationalmensday, heforshe, whywomendontreport, imwithher, mcug16, genderequality

Table 7: Top 10 hashtags for GBV datasets.

Linguistic properties for GBV tweets. Next, we examine different language attributes associated with the set of hashtags under investigation. In particular we wish to *examine different interpersonal awareness and affect patterns of GBV hashtags*. As a preprocessing step, we remove retweet headers, screen names, and urls. We use the LIWC 2015 software (Chung and Pennebaker 2007) for our linguistic analysis. First, we measure interpersonal awareness based on **linguistic dimensions** including the frequency of usage of *1st person singular* (1st p. singular), *1st person plural* (1st p. plural), *2nd person* (2nd pp.) and *3rd person singular* (3rd p. singular) pronouns. We investigate **temporal references** based on the usage of past, present and future tenses. We consider two measures of affect: *positive affect* (PA), and *negative affect* (NA). Under the umbrella of NA, we examine three measures of emotional expression: *anxiety, anger*, and *sadness*. The average percentage of usage of linguistic pronoun dimensions and temporal references are depicted in Table 8 and the average corresponding affective attributes in Table 9. We note the following observations.

Observation 1: *GBV hashtags inspire both self-expression and communal attachment.*
Higher usage of 1st p. singular (e.g. I, me, mine) is associated with hashtags #notokay and #whyistayed. Moreover, #notokay, #whyistayed, and #beenrapedneverreported exhibit focus on past and present temporal forms. This indicates a recall of self-relevant information including current and previous GBV experiences. Examples include the following tweets:
"The first time I was harassed I was 5 yo and a boy looked up my dress and commented on my ass #notokay @kellyoxford"
"#WhyIStayed because he made me distance myself from everyone and he always told me If i left I would be alone..."
Higher usage of 1st p. plural (e.g. we, us, our) is associated

Hashtag	1st p. singular	1st p. plural	2nd pp.	3rd p. singular	past tense	present tense	future tense
#beenrapedneverreported	0.64	0.68	0.27	0.19	2.94	3.23	0.14
#heforshe	0.94	3.16	2.19	0.4	1.08	9.41	0.40
#ibelievesurvivors	2.16	0.27	5.58	0.33	2.81	8.84	1.60
#itsonus	0.79	2.77	3.06	0.11	1.51	10.23	0.51
#maybehedoesnthityou	0.71	0.08	9.15	6.45	1.36	11.24	1.30
#notokay	5.42	5.11	3.85	0.31	9.53	9.28	0.21
#stateofwomen	1.3	4.3	1.42	0.17	0.89	10.38	1.67
#whyistayed	5.42	0.56	0.88	2.85	4.55	6.74	0.66
#whywomendontreport	2.36	0.84	1.4	1.16	2.66	10	0.56
#yesallwomen	1.79	0.52	1.18	0.44	1.57	7.96	0.45

Table 8: Average linguistic dimensions and temporal references percentages associated with GBV hashtags.

Hashtag	PA	NA:	anxiety	anger	sadness
#beenrapedneverreported	6.36	1.73	0	1.73	0
#heforshe	6.46	1.07	0.09	0.5	0.12
#ibelievesurvivors	3.48	5.06	0	2.4	1.6
#itsonus	3.25	4.13	0.09	3.09	0.12
#maybehedoesnthityou	2.63	6.74	0.88	2.68	1.14
#notokay	4.81	4.07	0.13	3.46	0.24
#stateofwomen	4.70	1.23	0.05	0.76	0.22
#whyistayed	3.24	5.69	1.4	2.55	0.43
#whywomendontreport	2.53	7.4	1.15	4.92	0.6
#yesallwomen	5.28	3.59	0.37	2.23	0.46

Table 9: Average affective attributes' percentages associated with GBV hashtags.

with hashtags #notokay, #stateofwomen and #heforshe. This indicates a sense of greater social awareness and support within the anti-GBV community. This is anticipated in the context of anti-GBV campaigns (State of Women and HeForShe) where individuals provide support for each other. On the other hand, #notokay provided a virtual space for both self-reported GBV incidents and mutual support. Examples include the following tweets:

"@kellyoxford I want to thank you for starting #notokay ...It is one of the reasons I had the courage to write this http://ndsmcobserver.com/2016/11/remembering-my-racist/"

"MT @FLOTUS Together, we are stronger. Together we can change tomorrow. Stand with us: http://www.theunitedstateofwomen.org #StateOfWomen @USWomen2016"

With the higher usage of 2nd pp. (e.g. you, your), the hashtags #maybehedoesnthityou and #ibelievesurvivors were primarily used to provide greater social awareness in the context of GBV. #Maybehedoesnthityou was used to bring attention to other forms of non-physical relationship abuse and #ibelievesurvivors was used to shed light on sexual assault victims speaking up but not being believed.

"#MaybeHeDoesntHitYou but he's isolated you from and turned you against everyone who you care about"

"When your role models fail you, become the role model you wish they were. #ubcaccountable #ibelievesurvivors"

From a temporal perspective, we observe that the hashtags #itsonus, #heforshe, #stateofwomen, #whywomendontreport, #yesallwomen #ibelievesurvivors, and #maybehedoesnthityou focus more on present issues than past and future.

Observation 2: *Mixed positive and negative emotions present in anti-GBV posts.*

Hashtags with the highest PA include #heforshe, #beenrapedneverreported, #notokay, #stateofwomen. The tweets associated with #heforshe and #stateofwomen encourage men to take solidarity with women and the unity of women, respectively, hence the higher PA scores. Upon inspection of the #beenrapedneverreported tweets, we discover that the captured tweets in 2016 discuss the spread of GBV underreporting and urge others to spread the word; these tweets rarely contain self-reported stories. On the other hand, hashtags with highest NA include #whywomendontreport, #maybehedoesnthityou, #whyistayed and #ibelievesurvivors. Most interesting are hashtags that combine both higher levels of PA and NA at the same time. These include #ibelievesurvivors (PA = 3.48, NA = 5.06), #itsonus (PA = 3.25, NA = 4.13), #notokay (PA = 4.81, NA = 4.07), #whyistayed (PA = 3.24, NA = 5.69) and #yesallwomen (PA = 5.28, NA = 3.59). The tweets associated with these hashtags, in some cases, contain both PA and NA simultaneously as indicated in Table 9. In these tweets, users exhibit NA due to the nature of GBV reported issues but at the same time, they express optimism about either the notion of women speaking up and sharing their personal experiences or hope for a change in their partners or the overall GBV situation. An example is the tweet: *"RT: KellyOxford: I am in such horrendous shock and yet so proud of the women* *sharing their assaults. #notokay is trending in US. Not our shame anymore"*.

Observation 3: *Anger is more prevalent than anxiety and sadness across all GBV hashtags.*

Among the negative affect attributes, we examine anxiety, anger and sadness attributes as computed by the LIWC software. Hashtags with the highest score of anger included #whywomendontreport, #notokay, and #itsonus. We also observe that the average anger scores are greater than anxiety according to Wilcoxon-Mann-Whitney test ($U = 6.0$ and p-value $< .001$) and the same for sadness scores ($U = 5.0$ and p-value $< .001$). Examples of tweets with high anger scores include:

"Is there One woman out there that has not been violated? *#YouOkSis #WhyWomenDontReport #WhyILeft #WhyIStayed #RapeCulture"*

"Under no circumstance is assaulting a woman acceptable. Abuse is abuse. Rape is rape. No means no. https://amp.twimg.com/v/1cf894c7-e211-4415-a809-d6ae71cd6ded #ItsOnUs"

Discussion

Digital Storytelling. In our investigations, we did encounter tweets of women sharing their personal assault stories as a part of the #notokay and #whyistayed hashtags, among others. This gives a new perspective on the role of digital storytelling in the context of GBV. Narrative and storytelling have played a huge role in the contexts of social justice (Bell 2010) and social movements (Davis 2002). Until recently, online platforms have been used to encourage users to anonymously share their harassment stories, resulting in shifting their cognitive and emotional orientation towards their experience (Dimond et al. 2013). What was intriguing in this case was the rise of non-anonymous self-reported stories, which can be viewed as a social movement by women expressing anger about the occurrence of GBV.

Public Figures and Digital Activism. Public figures played a vital role in encouraging people to take a stand against GBV. Four of our GBV-related hashtags (#notokay, #whywomendontreport, #maybehedoesnthityou, and #beenrapedneverreported) were inspired by public figures. We also note that public figures use Twitter as a channel for *digital activism* and promoting collective action in the GBV context, as in: "*In October I asked if we could all share our stories of sexual assaults. #notokay was born. Can you March on Washington JAN 21 with me?*", written by Kelly Oxford.

Limitations and Critique of Methodology. There are limitations to our methodology and findings. Recent studies (Tufekci 2014; Morstatter et al. 2013) discuss common issues associated with social media analysis and sample quality of the Twitter's Streaming API. We cannot claim to have captured a complete representation of GBV on Twitter or in the physical world, as we highly depended on the set of GBV key-phrases provided by UNFPA domain experts in (Purohit et al. 2015) as a starting point to our analysis. Our primary objectives were to investigate engagement patterns with GBV content and analyze gender and age demographics. The realm of GBV-related social interactions is clearly greater than what can be captured by a single platform; however, Twitter enables public visibility for user-generated content and the platform has played a key role in enabling women to share. Hence, Twitter is an excellent starting point in our attempt to understand GBV nuances as they take place over a single platform.

Conclusion

We provide some of the first empirical insights into social media discourse on the sensitive topic of GBV. In our analysis, Twitter has provided a powerful reflection of multiple aspects of GBV. While our analysis shows more engagement with GBV tweets in comparison to generic tweets, the engagement is not uniform across all ages and genders. Although Twitter has been an open platform for all sorts of discussions, it is only recently that public figures have encouraged people to share their personal stories. The data derived from our analysis can be used to complement policy design data sources. Our results show the need for more policies and programs that work to combat GBV. We also note that anger often surfaces in GBV content. It is our hope that this anger will lead to further progress towards raising awareness and eventually eradicating GBV.

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