Truth and Travesty Intertwined: A Case Study of #SSR Counterpublic Campaign

Kumari Neha*, Tushar Mohan*, Arun Balaji Buduru*, Ponnurangam Kumaraguru†
*Indraprastha Institute of Information Technology, Delhi, India
†International Institute of Information Technology, Hyderabad, India
{*nehak, tushar19393, arunb*}@*iiitd.ac.in*
pk.guru@iiit.ac.in

***Abstract*—Twitter has emerged as a prominent social media platform for activism and counterpublic narratives. The counterpublics leverage hashtags to build a diverse support network and share content on a global platform that counters the dominant narrative. This paper applies the framework of connective action on the counter-narrative campaign over the cause of death of #SushantSinghRajput. We combine descriptive network, modularity, and hashtag based topical analysis to identify three major mechanisms underlying the campaign: generative role taking, hashtag-based narratives and formation of alignment network towards a common cause. Using the case study of #SushantSinghRajput, we highlight how connective action framework can be used to identify different strategies adopted by counterpublics for the emergence of connective action.**

***Index Terms*—Social Computing, Data Mining, Online Social Media, Computational Social Science, Social Media Campaign, Counterpublics, Network Analysis, Sushant Singh Rajput**

I. Introduction

Sushant Singh Rajput (SSR), a Bollywood actor and celebrity, was found dead in his Mumbai apartment on June 14, 2020 [1]. Celebrity suicide deaths produce numerous posts on Twitter [2], and increase search on the internet over suicide and depression-related terms [3]. The death of 34-year old actor was reported as a case of suicide. However numerous dark conspiracies triggered on social media, including debates of nepotism [4], and possibly being framed [5] or murdered [6]. A combined study of prominent news channels and politicians over the SSR controversy revealed that the commentators over the topic were rewarded with higher retweet rates, which can be attributed to the widespread discourse engagement [7].

This study focuses on the social media users' narratives that followed after the actor's death broke on news and social media. The narrative included counterpublics [8], defined as marginalized communities that distribute messages to diverse social groups, raise awareness, and challenge dominant narratives. A Twitter user involved in activism activities such as organizing online petitions and building a counterpublic campaign narrative through hashtags is defined as a Twitter activist [9]. Our study aims to reveal the strategies adopted by the Twitter activists (i.e., counterpublics) to share, spread, and mobilize the support of the counterpublic campaign about the untimely death of the Bollywood actor.

We use the connective action framework to identify the roles activists play to facilitate interactions and build the campaign's momentum [10], [11]. Connective action comprises of networked and decentralized actions of mobilization in contrast to the traditional collective action characterized by centralized resource mobilization or led by a formal organization [12]. The most crucial aspect of the emergence of connective action is the rise of self-claimed activists who co-ordinate themselves, challenge the formal organization, and conduct a campaign [10]. Counterpublics have been found to form retweet networks on social media to gain legitimacy [13] and recommend relevant messages to the supporters of the campaign [14]. Connective action holds an assumption of a decentralized network since the activists who participate in the campaign are self-motivated to participate [15]. The user retweet network can therefore be used to analyze the organizational structure of the campaign [11].

We adopt a network perspective to unpack the three major mechanisms of the connective action framework. We focus on the activists and their content posted to understand the first mechanism (i.e., *generative role-taking*) underlying the connective action. When users on social media use common hashtags, it creates a context for like-minded people. The connection of the like-minded individuals thus gives rise to networked public [11], [16], [17]. We divide the networked public into two categories, information generators, and information drivers. The information generators work on content creation, while the drivers engage in driving the discussion by retweeting the content. To inspect the second mechanism (i.e., *hashtag based storytelling*), we perform an evolutionary analysis of hashtags used in the campaign. We divide the hashtags into buckets based on their mutually exclusive appearance in the tweets and use topic modeling on the content

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TABLE I: Table showing the bucket of hashtags in the counterpublics campaign against the dominant narrative.

Hashtag bucket	**Hashtag variants**	**Tweet count**
#candleforssr	#candle4ssr, #candleforsushant, #candle4sushant, #candles4s	$543,897$
#justiceforssr	#justiceforsushantsinghrajput, #ssrkoinsaafdo (give justice to SSR), #arrestcul-pritsofssr	$11,622$
#sushantsinghrajput	#sushantsinghrajpoot, #sushantinourheartsforever, #ssrians, #sushanthsinghraj, #shushant	$20,486$
#bollywood / #me-dia	#akshaykumar, #salmankhan, #kanganaranaut, #bollywoodpakisilink, #rheachakraborty, #ankitalokhande, #boycottkhans	$4,064$
#cbiforssr	#cbienquiryforsushantsinghrajput, #cbiivestigationforsushant, #cbicantbede-niedforssr, #cbienquiryforssr	$1,904$

shared among the buckets to identify topics focused on in the different buckets. The third mechanism (i.e., *formation of alignment network*) focuses on how the activists use social media for issue alignment and achieve virality. Identifying the fellow activists who also support the cause is crucial to achieving a collective goal (i.e., virality) [10]. We thus use community detection to identify sub-communities within the activist community to account for the diversity of users involved in the campaign. We also focus on how the narratives differ among sub-communities and examine any patter within and among sub-communities.

This study thus expands the literature of connective action framework and counterpublic campaigns and asks the below research questions:

- RQ1: What is the organizational structure of the social media counterpublic campaign around the death of Singh Rajput (SSR)?
- RQ2: How did hashtag-based storytelling evolve during the counterpublic campaign?
- RQ3: How did the campaign activists with different perspectives achieve issue alignment on the topic?

In the rest of the paper, Section II describes the collected data. We present the methodology used in our analysis in Section III. We further discuss the obtained results in Section IV and conclude the work in Section V.

II. Data

The time duration of data collection coincided with an increase in the media coverage and counterpublic narratives on Twitter. We used the Twitter search API to collect the tweets about the topic through trending hashtags which included #candle4ssr, #justice4ssr, #ssr, #sushantsingrajput. We curated a total of $1,027,213$ tweets from $67,822$ users using the official Twitter API. The duration of data collection spanned approximately 102 days from July 17, 2020, to October 21, 2020. The tweets consisted of $76,781$ original tweets and $950,432$ retweets. Any random tweet, on average, consists of 14.9 words, giving a good window for analysis of the user's thoughts around the campaign.

A. Pre-processing

Before performing any analysis on the collected tweets, we converted all the tweets into lower-case, removed stop-words, and removed any occurrence of URL from the tweets. We removed any tweet with less than 3 words to keep informative tweets for further analysis. We also removed tweets with hashtags with a frequency less than 100 in our dataset. The selection of the most frequent hashtags served to identify the narratives that became popular. The hashtags belonging to a bucket were identified based on a common theme (e.g., Bollywood and media cover hashtags with movie actors or journalists) or a different variation of the same keyword (e.g., candle4SSR written as candleforssr or candle4shushant written as candleforsushant) as shown in Table I. Tweets that used hashtags from more than one bucket were excluded from the analysis due to limitation of intention understanding that may require looking beyond the hashtag usage.

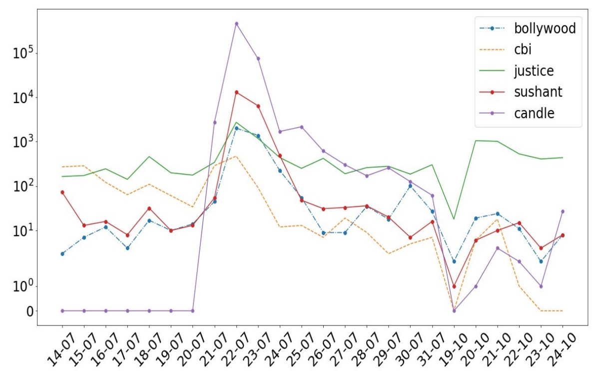

Fig. 1: Evolution of counterpublic campaign over the period of three months with respect to hashtag buckets as presented in Table I

We construct a retweet network from the person who posted the message to the user who retweeted the message to capture information sharing activities for a message-motivated communication. The retweet network is directed and weighted, where the direction indicates the flow of information, and weight indicates the number of retweets between the two users.

III. Methodology

We use descriptive network analysis coupled with modularity analysis and hashtag-based topical analysis to examine

TABLE II: Network descriptive statistics for the top information drivers and generators to understand the organizational structure of the counterpublic campaign. $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$ analyzed using unpaired Mann–Whitney U test. SD stands for Standard Deviation.

Metric	Top Information Generator		Top Information Driver		p
	Mean	SD	Mean	SD	
Active Days	7.65	20.19	12.05	24.94	$***$
Number of Followers	8024.8	107137.7	122.084	351.87	$***$
Number of Followees	479.54	3278.9	136.861	336.64	$***$
Number of Tweets	8225.29	22076.6	9204.433	14673.42	$***$
Indegree Centrality	8.37	0.0002	0.0013	0.0052	$*$
Outdegree Centrality	8.37	0.0018	0.0013	0.0042	$*$
Betweenness Centrality	4.86	1.50	1.29	0.00013	$***$
Closeness Centrality	0.003	0.0012	0.015	0.016	$***$
Eigenvector Centrality	0.0012	0.0035	0.0024	0.0097	$*$

strategies used by Twitter users to build collective agenda and mobilize attention. We first make a user retweet network that consists of $79,170$ nodes and $490,910$ directed and weighted edges.

To answer RQ1, we examine the overall network structure and information flow of the tweets among counterpublics. We also identify the most active hashtag activists from the collected dataset, defined by activist's in-degree and out-degree centrality scores. While the in-degree centrality captures the level of user initiative in information sharing, the out-degree centrality accounts for the influence and communication power of the activist.

For RQ2, we bucket the hashtags according to their mutually exclusive appearance. Social media users created numerous hashtags relating to the Bollywood actor. Selecting only the popular hashtags was to identify the narratives that went popular during the campaign. The final set of hashtags' buckets used for the study is presented in Table I. We further analyze the content of the tweets from different hashtag buckets to understand the dominant narratives around the hashtags.

To examine RQ3, we apply community detection on the retweet network to discuss how the counterpublic campaign narratives differ among the sub-communities. For community detection, we use CNM (Clauset-Newman-Moore) greedy modularity maximization algorithm [18]. CNM is a bottom-up agglomerative clustering algorithm that maximizes the modularity [19] of the community structure in a greedy manner. Once we have identified the sub-communities, we examine how the topics presented by the sub-communities differ for detecting alignment in the sub-communities.

IV. Analysis

A. Network descriptive analysis

The descriptive network analysis of a network can help identify the user dynamics and their clustering patterns during the online campaign. We present the descriptive analysis of the retweet network of the counterpublic campaign in Table III. The retweet network was found to be very sparse, with a network density of 0.000078. The sparseness in the network is expected given the large number of nodes and edges in the network. Usually, the retweet network tends to cluster rather than being evenly distributed, which can indicate the formation of an echo chamber around a topic [20]. The average in-degree and out-degree centrality for the activists were 7.83, which indicates that the average connection between activists for either retweeting or being retweeted is equal. The average clustering coefficient for the network is 0.060, which is very low. The low clustering coefficient indicates that all the activists are not well connected. Based on the out-degree centrality, a single user's highest number of retweets is $23,210$. While based on the in-degree centrality, the activist who retweeted the maximum times is $1,253$.

The in-degree centralization of the network is 0.0065, while the out-degree centralization for the network is 0.29. A higher out-degree centralization indicates there were a set of users who were more frequently retweeted than others. Comparatively, a lower network in-degree suggests that the activists were more or less equally active while retweeting about the campaign. This result indicates the evidence towards slacktivism, which is defined as actions that require minimum effort and cost of participation like retweet since it does not require the user to write their own content [21]. Since the counterpublics were mostly slactivists, it suggests that the campaign's main goal was to obtain momentum and raise awareness about the campaign.

TABLE III: Descriptive statistics of the overall retweet network.

Metric	**Mean value**
Network Density	0.00078
In-degree Centrality	7.83
Out-degree Centrality	7.83
Clustering Co-efficient	0.060
In-degree Centralization	0.0065
Out-degree Centralization	0.29

To answer RQ1, we divide the activists involved in the

(a) #candleforssr (b) #bollywood (c) #cbiforssr (d) #justiceforssr

Fig. 2: Word clouds for narrative hashtag bucket from Table I.

counterpublic campaign into two parts based on their in-degree and out-degree centrality measures. We select the top 1000 activists in our dataset based on their in-degree and out-degree centrality. The top 1000 users with a high out-degree centrality are referred to as top information generators, and the top 1000 users with the highest in-degree centrality are referred to as top information drivers. We analyze the descriptive network statistics for the top information drivers and generators to understand the organizational structure of the counterpublic campaign. The descriptive network statistics for the top generators and drivers are listed in Table II. Based on the descriptive statistic analysis summary of the activist's attributes, a typical information generator was active for 7.65 days, had about 8,024 followers, followed 479 users, and tweeted 8,225 times. While, on the other hand, a typical information driver was active for 12 days and had a comparable follower-to-followee ratio. Mann–Whitney U tests were performed to examine whether the difference between information generators and information drivers are significant or not. We perform Mann–Whitney U tests since the test does not make any inherent assumption about the distribution of the population. We found that there is a significant difference between the active days, the number of followers, and the number of followers as shown in Table II.

Although the average number of days a user participated in the campaign is low for both drivers and information generators, we found that the drivers were more active than the generators. From the eigenvector centrality score, we can conclude that since the information driver's score is more than the generator's score, drivers are more actively connected with other active campaign activists. However, the betweenness centrality for a generator is more than the driver, indicating generators are more likely to have a shorter path between two activists. The active retweeting of the campaign hashtags and a mix of centralized information aggregation and decentralized information generation are key to the formation of connective action.

B. *Evolution of the counterpublic campaign narratives*

To analyze how the counterpublic campaign evolved over the period, we plot the frequency of narratives' buckets identified through hashtags in Figure 1. The division of hashtags is presented in Table I. We found that all the hashtags, in general, saw a spike between July, 20, 2020 and July 24, 2020. The tweets with hashtags #cbiforssr and #justiceforssr were initially used more; however, during the period of highest frequency, #candleforssr was used most times. The use of #Bollywood hashtags also rise during the spike. #justiceforssr, however, was the most consistent hashtag bucket throughout the data collection.

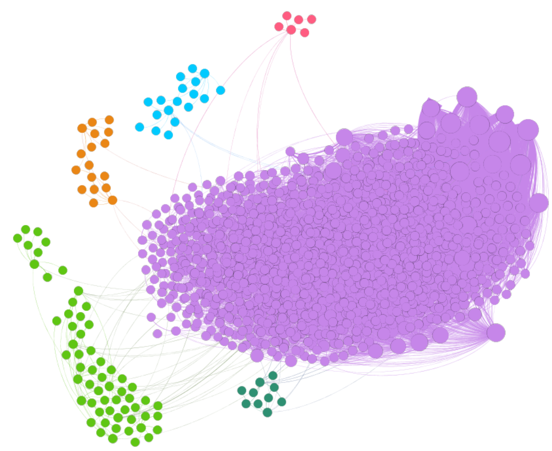

Fig. 3: Figure showing the community formed among top information generators and their top drivers. Each color uniquely identifies a sub-community. Sub-community 1, shown in purple, constitutes 92.96% of the users. The second sub-community, shown in green, constitutes 4.15% of the users. While blue sub-community includes 1.27%, orange comprises 1.2%, dark green comprises 0.7%, and pink sub-community comprises 0.42% of the users, respectively.

To understand what narrative was spread in tweets within the hashtag buckets and how they differ, we plot the word cloud of the tweets from hashtag buckets as shown in Figure 2. The dominant narrative from #candleforssr was the declaration of online protest against the debate of suicide of the late actor. As shown in Figure 2c, the #candleforssr bucket revolves around demanding justice, mobilization through participation, and mention of debate and journalists (e.g., Arnab Goswami). The #justiceforssr bucket showed some narratives similar to #candleforssr, in addition to mentioning influential people, murder conspiracy, and shades at Mumbai police as shown in Figure 2d. The #bollywood bucket in Figure 2b, mainly included tweets mocking other Bollywood celebrities and despising nepotism. #cbiforssr, which was one of the first spikes in the dataset, consisted of tweets about inquiry, involvement of CBI (Central Bureau of Investigation), and topics of justice, protest, and nepotism as shown in Figure 2c.

C. Issue alignment among the counterpublics

We used the top 1000 generators and their top 10 drivers to identify whether there is the formation of any sub-community within the network and whether different sub-communities share different narratives. The reason for selecting the top generators is to account for the most popular content in the campaign. We apply CNM algorithm for community detection [18] among the counterpublics. The number of iterations for the community detection algorithm was 100. The average clustering coefficient was found to be 0.021, with average degree as 14.075, modularity as 0.35 and network diameter as 9. We found 6 sub-communities in our user-retweet network as shown in Figure 3 with each community represented by a different color. The retweet network of top generators is densely connected, which shows evidence for a connective campaign and a leaderless information-sharing framework. A few nodes with less connection indicate a centralized structure where information is being shared from few generators to many drivers. The formation of the dense cluster is evidence for connective action. We further perform LDA [22] on the combined tweets of top 1000 generators and top 1000 drivers to identify the major topics they share in the online environment.

TABLE IV: Table with topics discussed among top 1000 information generators and drivers respectively.

Justice	singh, world, justice, protest, digital
Candle	supporting, hope, smile, many, stand
Support$_T$	tweets, guys, digital, protest, million
Support$_C$	comment, below, million, reach, post
Media	arnab, goswami, debate, worldwide, live
Support	dead, watching, where, living, duty, suicide

Among the top 6 topics from the LDA as shown in Table IV, 3 dominant topics revolved around online mobilization represented as Support$_T$, Support$_C$ and Support. In the 3 mobilization topics, the social media users requested SSR fans and fellow social media users to retweet the content for widespread dissemination of information. While Support$_T$ encouraged to tweet about the campaign, Support$_C$ suggests commenting on the posts to gain momentum on social media. In the topic Support, the counterpublics used words like duty and watching to encourage fellow campaigners and social media users to participate. The other 3 topics were identical to #justiceforssr and #candleforssr buckets, which were the two most prominent narratives in the overall campaign. The topic represented as Media included the debate led by news media on the investigation of the suicide.

TABLE V: Table with topics discussed among sub-communities.

Protest	protest, want, world, justice, digital, love, tweets
Media	arnab, know, rhea, raha, pagal (mad), aadmi (man), badla (revenge), will
Nepotism	money, huge, production, extract, houses, handle
Candle	light, candle, support, thank, fight, unity, hope, march

To answer RQ3, we first run the LDA on the tweets from each sub-communities. Given that the people who were retweeting each other would belong to the same sub-community based on modularity analysis, the same set of tweets are expected from a given sub-community to remain connected. We set the number of topics as 3 with 10 words in each topic. To find the alignment among users from the 6 sub-communities, we identify the common topics in all the sub-communities. We found that users from sub-communities tweeted or retweeted more or less on the topics presented in Table V indicating an inter-connected community structure and issue alignment in sub-communities.

V. Conclusion

We apply the connective action framework to analyze the counterpublic campaign on online social media through a case study of the untimely death of Sushant Singh Rajput (SSR). We uncover the conditions under which hashtag activism can turn into connective action. With the help of a network-based approach, we investigate the users and their content simultaneously and identify three mechanisms of the connective action framework: generative role-taking, hashtag-based storytelling, and issue alignment among the different diverse groups of activists. To identify generative role-taking, we construct a user retweet network. We found that while top information generators tend to have a shorter path to any fellow activist, the top drivers are more actively connected. The most consistent hashtag used for the counterpublic campaign was #justiceforssr, while #candle4ssr had the highest peak. Lastly, the community detection indicates clique formation in the retweet network, where most of the top generators are densely connected, while a few having a sparse connection.

The community of counterpublics thus indicates a mix of centralized and decentralized information aggregation with a strongly connected network with no standalone communities present.

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